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TEXTURE BOUNDARIES IN DIGITAL IMAGES

by

© GERALD G. TYCHON

A THESIS

SUBMITTED TO THE FACULTY OF GRADUATE STUDIES AND RESEARCH
IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE
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FACULTY OF GRADUATE STUDIES AND RESEARCH

The undersigned certify that they have read, and recommend to the Faculty of Graduate Studies and Research, for acceptance, a thesis entitled "Texture Boundaries in Digital Images", submitted by Gerald G. Tychon in partial fulfilment of the requirements for the degree of Master of Science.

ABSTRACT

This thesis is concerned with the determination of boundaries between adjacent textured regions in digital images. Boundaries or contours separating regions provide, in general, the most important information in a scene and the reason why their determination and extraction is useful. The extraction of boundaries is accomplished by generating 2nd-order pictures from an original textured image. Eight 2nd-order pictures are generated, two for each orientation of 0°, 45°, 90°, and 135°. For each orientation one picture contains frequency information and the other contains contrast information. The pictures are obtained using relatively simple statistical measures which are applied to a neighbourhood about each and every point in the original picture. The values produced by the measures are obtained directly from the picture element values without the use of training samples and are of a type and range such that they themselves form a picture. The 2nd-order pictures are then manipulated and processed by means of picture smoothing, thresholding, gradient edge detection, and then combined to produce a single final edge picture.

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CHAPTER 1

INTRODUCTION

This thesis is concerned with the determination of boundaries between textured regions. Boundaries or contours separating regions provide the most important information in a scene and the reason why their determination and extraction is useful. Pictures which are highly textured usually pose problems not encountered in "ordinary" untextured pictures and must be approached differently if meaningful results are to be obtained.

When a gradient edge detector [Davis, 1975] is applied to a textured picture in an effort to find the boundaries between regions, the resulting edges may be unclear, nondistinct, or poorly defined. By taking into account textural clues these difficulties can be remedied. The approach used in this thesis specifies that textural measurements be generated which will themselves form a picture.[1] This "picture" can then be processed by conventional image processing algorithms such as smoothing,

---

[1] This idea has been briefly touched upon by Rosenfeld, Lee, and Thomas [1970, p. 382].

enhancement, or edge detection. By formalizing the idea of generating one image from another, different "orders" of pictures can be defined. A 1st-order picture is an original picture or a modified version of an original picture, where modifications can, for example, be linear transformations or smoothing operations. A 2nd-order picture is an image of a measure of a 1st-order picture.

Specifically, a procedure is proposed by which images containing adjacent textures can be processed or manipulated with the subsequent extraction of borders indicating where the textured regions meet. In other words, given a picture or scene which contains textured areas (that can be differentiated from each other by their textural components), it is possible by generating and analysing 2nd-order pictures to separate the areas and determine the boundaries of the textured areas. This is accomplished by performing a sequence of operations (smoothing, merging, edge detection) upon 2nd-order pictures which have been derived from a textured original (a 1st-order picture).

1.1 General Background

Having stated what the aim of the thesis is, it is appropriate that a few words be said as to what the field of image processing comprises. Image processing has, within the last several years, been a discipline coming into its own right with more and more uses and applications arising

every day. At present, a wide variety of areas of study use image processing techniques.[2] The medical field uses these techniques to aid in analysis of X-ray or other images made of the human body. Many other fields use image processing concepts when dealing with satellite and aerial pictures. Thus, in the areas of agriculture and forestry, the crops and soil, as well as the growth rate, type, and distribution of various trees and forests are being studied from air and space. In meteorology, the factors affecting and controlling the weather are being looked at. Maps are being made and terrain analysed in cartography. Geologists, assisted by image processing, look for land surface formations. Even archaeologists have been drawn into the area in trying to find historically interesting sites. A general viewpoint has work and activity in this area integrated with other areas of computing science to create image understanding systems. While this might not be accomplished in the immediate future, it does provide direction and a goal to unify the field.

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[2] Some references to the use of image processing techniques are: Medical - [Di Chiro, 1977; Herron, 1973], Agriculture and Forestry - [National Academy of Sciences, 1970], Meteorology - [Barrett, 1974; Yates, 1970], Cartography - [Quam and Hanhah, 1974; Wong, 1974], Geology - [Reeves, Kover, Lyon, and Smith, 1975], and Archaeology - [Gumerman and Lyons, 1971]. A reference to the general processing of satellite and aerial pictures is [Reeves, Anson, and Landen, 1975].

1.2 Aspects of Image Processing

To alleviate the possiblility of confusion or misunderstanding due to a lack of familiarity with image processing terminology or ideas, the next several subsections will give some background information and explain a few relevant image processing concepts and terms. In addition, terminology and notation specific to this thesis will be defined.

1.2.1 Basic Definitions

The following basic definitions and notation will be used in subsequent portions of the thesis. It is possible to consider a _picture_ or _image_ (these two words are used interchangeably) as being a real valued function (picture function) of two real variables defined in some spatial domain with brightness a function of the x, y coordinates. In the digital image case, there exists a digital picture function which is a discrete function of two variables with the sampling area divided into distinct picture elements. A _picture element_ is the smallest discrete point in a picture. For the purposes of this thesis, an _image_ or _picture_ is a two dimensional array of integers where each integer indicates a level of brightness for a location in the array. A more formal definition has an image defined as a two dimensional array as follows [Haralick, Shanmugan, and Dinstein, 1973]:

> "If $L(x) = \{1,2,\ldots,N(x)\}$ and $L(y) = \{1,2,\ldots\ldots,N(y)\}$ are the X and Y spatial domains, then $L(x) \times L(y)$ is the set of resolution cells and the digital image I is a function which assigns some gray-tone value $G \in \{1,2,\ldots,N(g)\}$ to each and every resolution cell; $I: L(x) \times L(y) \to G$."

The word _pixel_ or _pel_ is commonly used as an abreviation for picture element. The _grey_ (or _gray_) _level_ (or _value_) is the actual number associated with a pixel. The range of these numbers will usually depend on the equipment available. Two commonly used ranges are 0 to 63 and 0 to 255. In the work presented here, all grey levels are (due to hardware constraints) in the 0 to 63 range. The value 0 usually represents pure black or minimum illumination while the greatest value in the range is representative of white or maximum illumination. The intermediate values in the range represent varying shades of grey. A _binary picture_ is a picture whose elements have only two values (usually 0 and 1).

The _neighbourhood_ of a picture element refers to the picture elements contained within some region of interest around the given element. The size and shape (the boundaries) of this region are variable and depend on the application or need. The neighbourhood may, for example, be a rectangle, a star, or a cross.

A _histogram_ is a graphical means of displaying frequency distributions. A _picture histogram_ is used to indicate how many picture elements (for a given image)

possess a certain value. Thresholding refers to a process in which elements are separated into usually two, but sometimes more, classes. In the case of a single threshold with two resultant classes, those elements which are greater than or equal to the threshold (some number) are assigned a value (perhaps 1) and placed into one class while those less than the threshold are given a different value (maybe 0) and relegated to the other class. In the course of this thesis the following mathematical notation will be used, where A and B are expressions:

A * B - A is multiplied by B.

A ** B - A is raised to the power of B.

SQRT(A) - the square root of A.

ABS(A) - the absolute value of A.

SUM - represents summation (Greek capital letter Sigma).

1.2.2 Fundamentals

For clarity and completeness the following concepts are presented. Put succinctly, image processing is involved with modifying or analysing pictures in some way.[3] Activities which fall into this field may be classified into several interrelated areas. One of these areas is encoding and approximation. Here the information content of pictures

---

[3] Information on the general principles and techniques of image processing may be found in [Andrews, 1970; Lipkin and Rosenfeld, 1970; Rosenfeld, 1969; and Rosenfeld and Kak, 1976].

is measured and coded as compactly as possible. Approximations of pictures are studied so that one picture may be replaced with another which has a lower information content. Another area is that of *restoration*. This usually involves the removing or minimizing of any degradations in a picture. Related to this is *noise abatement* where attempts are made to reduce the effects of noise produced by, for example, components in some sensing apparatus. There is also an area called *image enhancement*. Improving the contrast of a picture and making edges more visible in a picture are included in this area. *Analysis* attempts to determine various characteristics of a picture. In some situations this may be done by looking at the various statistical distributions present in the image. Overlapping with other areas is *pattern recognition* and *picture description*. Efforts here are made to recognize patterns in, and properties of, a picture so that a description of the picture may be extracted.

The above different areas allow for numerous operations to be performed on pictures (e.g., in attempting to filter, restore, and enhance them). These operations may be distinguished as being either position invariant or position variant. The result of *position invariant* operations on a point in a picture does not depend on the location or position of the point in the picture. It only depends on the value of the point. Examples of this are smoothing or sharpening operations. Operations which are not position

invariant are called position variant. A general example of a position variant operation is one which corrects for variations or errors produced by the digitizing or sensing apparatus. A specific case being where an optical lens does not pass light uniformly, with the result that some portions of the digitized picture are brighter or darker than others, even though originally all regions provided equal illumination. In this situation an operation can be performed to compensate for the peculiarities of the lens.

Operations may also be described as being point, local, or global in their effect. In a point operation, a picture element value is changed in a way that is independent of any other values in the picture. With the use of a local operator, the effect on a picture element is dependent on the values in some neighbourhood around the element. Local operators which are position invariant are often placed in a category called spatial filters, or spatial frequency filters if they are carried out in the frequency domain. The frequency domain is a function which depends on the spatial frequencies contained in a picture. It is possible to think of this function as being the Fourier transform or frequency spectrum of a picture [Andrews, 1970]. In the case of global operators, a change in element value is dependent on all other element values in the picture.

1.2.3 Second-Order Pictures

Second-order pictures are measures of another picture. If one looked at a neighbourhood about each point in a picture and determined the difference between the maximum and minimum grey level values of elements in the neighbourhood and then output this value as a pixel, the effect would be to produce another picture which contains information about the first picture. This second picture can be called a 2nd-order picture and can be used to facilitate analysis of the 1st-order or original picture. By labelling these derived pictures 2nd-order, an attempt is made to formalize and describe certain aspects and procedures of image processing.

More tangibly, 2nd-order pictures can be used to help analyse difficult pictures. The generation of these pictures should be thought of as a step in problem reduction or analogous to top-down programming. In this case it can be referred to as top-down picture analysis. A difficult problem is being broken down into a number of (hopefully) easier problems which may then be solved and whose composite solutions yeild a solution to the original problem. In this case the difficult problem is the original picture which is to be analysed and the easier problems (subproblems) are the 2nd-order pictures generated. The production and manipulation of these 2nd-order pictures provides a method for the extraction of information from pictures with a

minimal or at least a smaller amount of specialized software, i.e., once the secondary pictures exist, fairly conventional image processing algorithms may be used.

1.2.4 Texture

Since visual texture is an important element of this thesis it is important that the reader understand what is meant or connotated by the word "texture". Texture is easily perceived by humans and yet is not so easily described. People know what it is when they see it, and it may be described as smooth, rough, coarse, irregular, structured, etc. Although texture is a property of almost all surfaces a good precise definition of visual texture does not exist. This is partly because it has not been necessary until the last several years to have such a definition. Also, the problem exists of getting agreement or consensus on such a definition.

Basically what exists are intuitive statements of what texture is or what conditions must be present for texture to be perceived. One statement proposes that texture exists when a large number of elements (consisting of spatial variations in intensity) are each visible to some extent and in general, are densely and evenly arrayed over the field of view [Pickett, 1970]. In the viewing area, repetition exists though not necessarily regularity. On the other hand, texture can be described as the spatial distribution

of tonal variations in some given area [Haralick, et al., 1973]. By tone, one means the changing levels of intensity of pixels within an image. While tone is varying shades, texture is varying spatial distribution of tone. These two ideas are intuitively related. If an area has little change in grey scale then the predominate characteristic is tone. Conversely if there is a large variation of individual grey tone then the characteristic property is texture. Some feel that texture has three properties [Hawkins, 1970]. First, there is some local shape which is repeated over an area which is large in comparison to the shapes size. Second, the shape is non-random in the arangement of its elementary parts. Third, the parts making up a shape are roughly uniform within the shape.

It is also possible to analyse texture in terms of the amount of information present in a scene. If a scene contains a "large" amount of information in a given area, then it can be said that this scene is textured. The question arises as to how large is "large". One possible solution is to have a numerical value for this "largeness" determined by empirical means. A number of textured pictures can be processed by means of an edge detection program and the resulting edge segments or points tabulated. The value obtained after testing a number of scenes, which are recognized as being textured, would be an estimate of the amount of information required. It follows from this that by using a threshold so derived, one could blindly test

a scene and determine if it is textured or not. This approach does not require knowledge of any patterns which may exist or how these patterns might be repeated.

Though a good solid definition of texture has not (as mentioned) at present been developed, this does not mean that research cannot proceed in this area. Techniques of texture analysis must be developed based on current definitions or descriptions [Meurle, 1970]. Any results obtained can then be used to create better definitons leading to the development of better techniques. Currently, it appears that our descriptive abilities and methodologies are simply not at an adequate stage of development to handle visual texture.

1.2.5 Meaningful Textures

Meaningful textures are those which have a non-random arrangement of their basic parts [Hawkins, 1970]. The small shapes or patterns used to make up the texture create a familiar impression on the observer. The internal structure can be easily described and it corresponds to some mental concept or idea. For example, when wood grain is mentioned, this immediately creates an impression which can be recognised and classified as mainly parallel lines which may be horizontal, vertical, or perhaps radiating out from some point. Similarly, sand or gravel will cause one to visualize an irregular, perhaps splotchy texture. It is

these meaningful or familiar textures which are most important to human beings and one reason why emphasis should be placed on them in computer analysis.

1.2.6 Natural and Artificial Textures

In addition to meaningful or nonmeaningful textures, one can also split textures up as being natural or artificial. Natural textures are usually those which occur in the "real" world. Often the repeated patterns in these textures are similar to each other but not identical, i.e., the patterns belong only to a similar class. In addition to the patterns themselves not being perfect, the spatial distribution is also nonperfect. The distribution may have variations due to phase shifts, distortions (such as stretching and twisting), and rotation.

In computer analysis, artificial textures are those which are generated with deliberation on a computer. These very often have have some elementary pattern repeated perfectly in an exact spatial distribution. This is of course not always true since it is possible to computationally create distortions such as may exist in natural textures. Sometimes random noise is introduced to purposely degrade the image.

Both artificial and natural textures can be useful when investigating computer and human analysis of texture. The use of artificially created texture allows for a closely

controlled data environment when testing and looking at specific aspects of interest. Natural textures, though more difficult to manage, are of importance since they occur in the "real" world and eventually must be dealt with.

1.3 Thesis Goals

Two specific objectives should be accomplished by implementing the ideas presented in this thesis. First, several kinds of 2nd-order pictures should be defined and generated. Then, in order to prove the value of the 2nd-order pictures, they are to be used to extract the boundaries separating different textured areas of an image.

By first formalizing the concept of (and then generating) 2nd-order pictures, a tool is being provided by which pictures may be analysed. It is hoped that by using these generated pictures, it will not be necessary to have programs or techniques which have to be constantly varied according to the type or class of image being investigated. Instead of developing new techniques to handle some difficult picture category, 2nd-order pictures are generated and then conventional image processing techniques used. With images that are textured, if 2nd-order pictures can be used to find the boundaries between textured regions, then it is only a small step to using the secondary pictures to find the size of the textured regions or even to extracting the regions from the original picture.

1.4 Summary of the Thesis

Chapter Two focuses on how humans perceive and understand texture. Discussed are the different levels and components of perception, how texture helps perception, and how perception is affected by the surface slant, density, and arrangement of elements in texture. In addition, a view on textural elements and how they are grouped is included. After this, discussion proceeds to contours in texture, their importance, their type, and how they are grouped.

Chapter Three is concerned with computers and texture. It begins with the means by which computer algorithms identify and classify texture. Following this is a discussion of various aspects of texture and approaches to texture analysis using computers. Examples include work on texture coarseness, extraction of edges surrounded by texture, and the use of texture as a depth cue. Subsequently, texture generation and a few theoretical aspects concerning texture are discussed. The chapter concludes with some of the unresolved problems associated with computers and texture.

In Chapter Four the generation of second-order pictures and their application to textural boundary determination is presented. What measures are used, how the measures are applied and what is done with the results of these measures (such as smoothing, gradient edge detection, and merging of pictures) are discussed. There is also an examination of

the data used, its representation, the sources of the raw data, and its manipulation to produce test data.

Chapter Five presents pictorial results which were produced by the techniques introduced in the thesis. An analysis and discussion is included with the pictures, as well as tables that summarize and further illustrate information in the pictures.

The last chapter offers conclusions regarding the work and results of the preceding chapters. In addition, a section details what further work may be done in this area and other related areas of image processing.

An appendix discusses pertinent hardware and software considerations. This includes a look at the two main hardware facilities employed, the software available on the hardware, and the reasons why certain hardware and software combinations were used. There is a list describing the functions of programs which were designed and implemented.

CHAPTER 2

TEXTURE AND HUMAN VISION

How human beings perceive and analyze texture is presented in this chapter. Discussion is included on the levels of human visual processing, the perceived appearance of textured surfaces, the importance of element contours within texture, and how these contours are grouped to give a general impression. It is hoped that by comprehending how humans perceive and process visual texture information, understanding of texture in general will be improved and it will be possible to perform computer analysis in a more effective manner.

2.1 Levels of Human Perception

Human perception, for the purposes of this thesis and visual texture analysis, can be broken up into two levels called primary perception and secondary perception. These two levels are connected as shown in Figure 2.1.

Primary perception seems to operate in parallel with many pieces of information processed simultaneously [Anderson, 1975]. The light stimulus is converted into

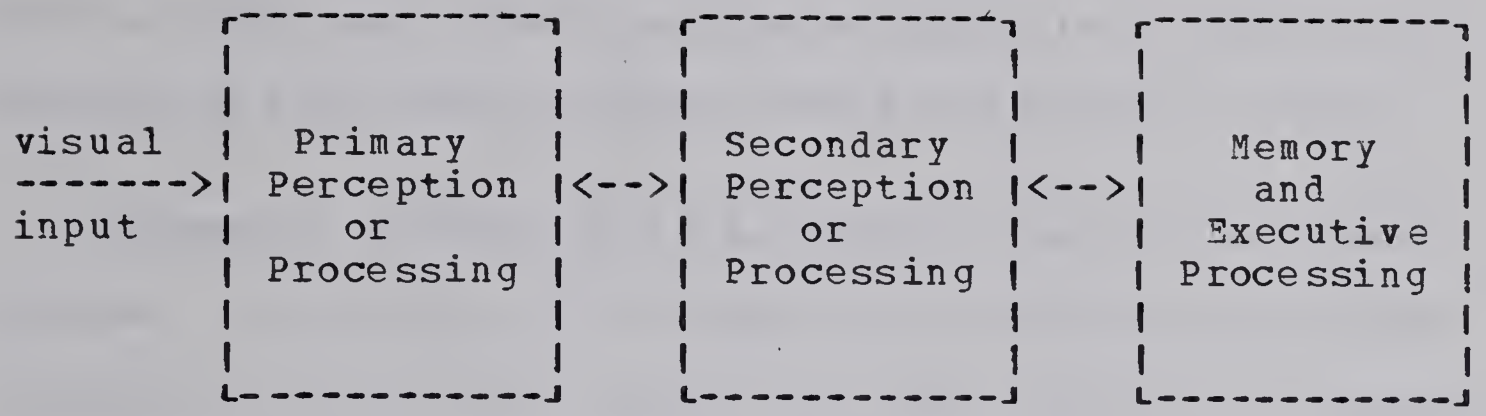
visual input
Primary Perception or Processing
Secondary Perception or Processing
Memory and Executive Processing

Figure 2.1 Levels of Perception

neural activity, which is then treated as information in a parallel processing system. It can be said, with some reservations,[1] that this primary process is innate, i.e., humans are born with it. This inborn system operates rapidly to produce crude, wholistic pictures of the surrounding world with built-in mechanisms operating automatically to analyze features of brightness (tone),

---

[1] Some controversy has arisen due to experiments conducted on cats [Lewin, 1974]. When a new born cat is presented with a visual world which consists entirely of vertical stripes for a period of time, it either does not gain or it loses the ability to detect horizontal stripes. While there is no solid evidence to indicate whether this is due to the failure of cells to develop or whether it is due to the attrition of unstimulated cells in the cortex, present belief favours the latter theory.

colour, length, and motion. Analyzers in this system which respond to stimulation for a given retinal position feed into more general analyzers which are then independent of retinal position. These analyzers appear to be inate and located in the visual cortex[2] [Hubel and Wiesel, 1972].

Secondary perception is basically a serial processing system. Its function is to select and combine information produced by the primary system and then relate it to memory. The information is selected and combined one piece at a time.

These two levels of processing are related to the two types of human textural analysis [Pickett, 1970]. The first type is *impressionistic*. This corresponds to primary processing where a large amount of processing is accomplished in a short period of time to produce a general understanding of a scene. From this we can get a basic impression of a texture. The second type is called *deliberate*. This corresponds to secondary processing and describes a conscious analysis of a scene usually involving inspection of elements within the scene.

These two types of analysis are illustrated in Figures

---

[2] The word cortex refers to the several outer layers of nerve cells composing the brain. On the whole, different portions of the cortex are responsible for different functions, e.g., speech, hearing, touch. The area of the cortex which is concerned with vision is located at the lower back of the brain and is referred to as the visual cortex.

2.2 and 2.3, respectively. In the first of these two figures, a quick glance is sufficient to determine the existence of two distinct regions, one embedded within the other. This figure amply illustrates the principle of good Gestalt [Moore, et al., 1975; Preston, 1976]. A region or shape, and its background are said to possess good Gestalt if individually the shape and background can be detected in the combined or composite image. In the second figure the initial inpression is a uniform texture made up of numerous letters of the English alphabet. It is only after a closer scrutiny of the elements comprising the texture and their location that it is realized that there are four distinct regions defined.[3] The four regions are the four quadrants of a square. The top left and bottom right quadrants are comprised of the letters A to M and the top right and bottom left quadrants comprised of the letters N to Z.

2.2 Components of Perception

Earlier discussion illustrated two general levels of perception, which operate together to allow perception and understanding of scenes. In this process of understanding it is possible to think of three kinds of information which can be obtained from a scene, or alternately the scene contains three types of information or three features

---

[3] A different example of deliberate analysis of texture which uses regions of semantically meaningful and non-meaningful words may be found in [Juliez, 1962].

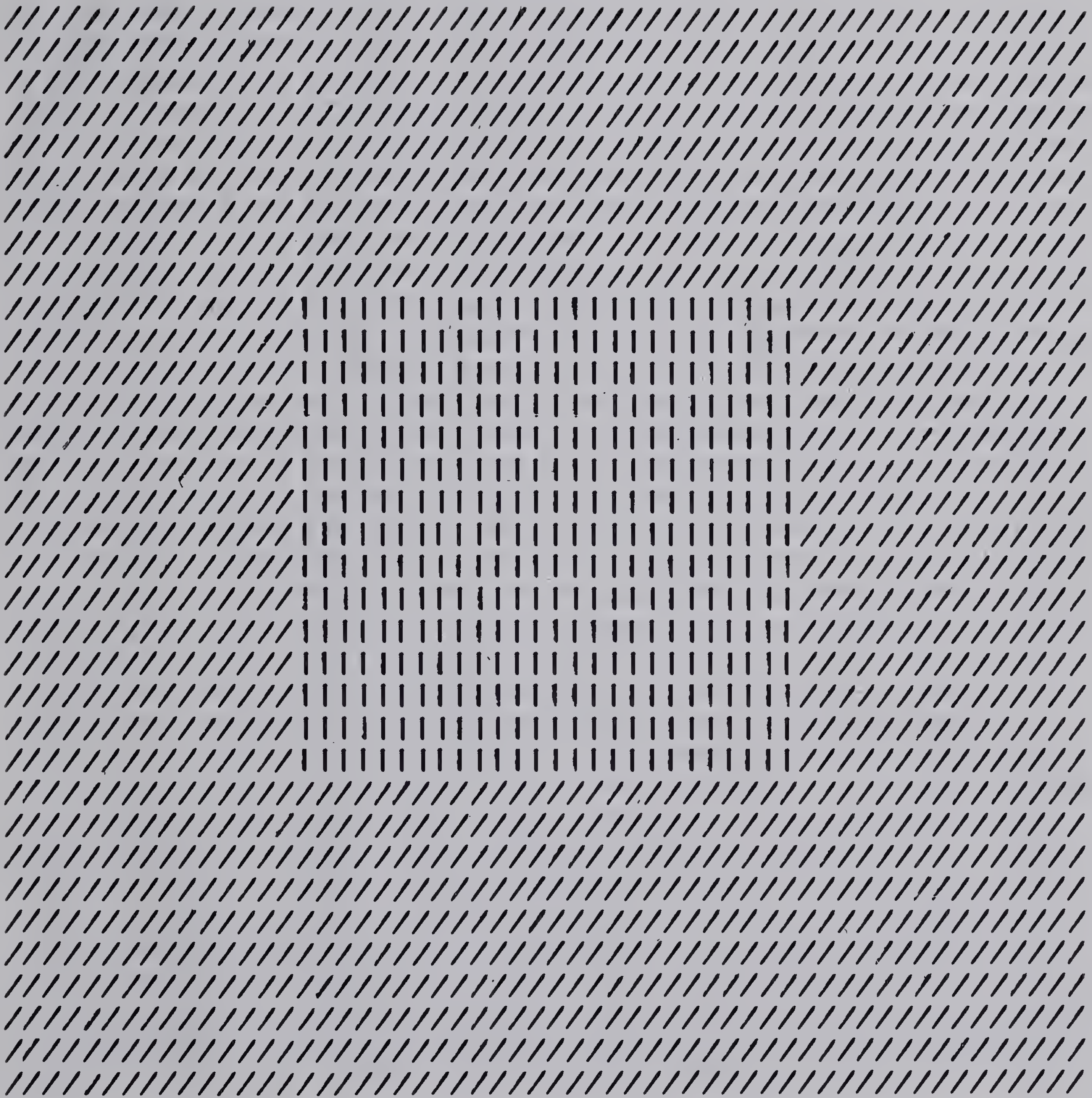

Figure 2.2 Texture Requiring Only Primary Analysis

```
DBCIGBDLKCHAJDGECEMDIBHKHCKMXYQXZRWVPUXVVOOOWOSTXXWQOQXW
GGDECMMFGCBLFMAHKGEDHBFEMBLBQQUXUSYYORZQQWOPOURNTUPPONTR
ECKMBAGBBGICFLIIAGFICGGJHLEHSUNUXNYZVWVSRQVOOYRUUVWNNYQQ
DIDIIBAIBGIHMECGCJLGAFGGIEBCTTUUZUUZYWOVYWPUUVUWUNWVZTUS
HFFCJLIFGJAMCCMELIDAKILEDBFHQUVYNWWWXWSPYUOTOOOYQXYZPYXY
EIHHLHCHAAICCGFKIDDMHIGBCKEJPZYUYOYUQSSOXTSUVXOUNSZQYNPV
FMCBHMFJGGIEJHLAJBHKKFGBCCKASVRQQPZWSRZPYTZSUQQPPXVZRNUY
GHIECKEFFKEAFFJADGHIDBKAEHJJUWVTOSVVXNPSTNQQQRSNUURVNTSX
CLFABLKCKIJMFIMGJMMEKKEDLJKDOYORYSONWZPTUSYTOYURTQONRUPS
HDBEHDGHFKBGIJKEMCEHCLEKJILMNZOWTTRRPUQOQPRXWYWWONNZRPUT
BKCMEKGDGHADIBJMIGCFDHLJJJFCPXWTYZTWRWUWYTOTWYNPXROVUVVQ
CADDEEHILGCMBACGMFDGMEKBDCADNUNXOXNNSVUTYZUYQORSXTXSSPNY
GKBLFHGLCHFKJKCHCJEKEDEBCJBHZTWQRNWTZUYQVNSRZYQVWQNYQXRV
GGDCBEEEDICBFGKKACBMEGADIDGLZUTTQONVOOORZRUUROZYPNRUQTRS
MCHKALKJCDDDLHJFJMKMJEJLFCBJQZPVYSVWTQRXQOPNRFNWTRYVOYRO
CAFLCAIAJKCJLBFFHGDHLGJDECMDZSYYTVOZVSYYUTZRYUOSXNQOYOSY
FGJCBJJAFJAACHCKFMFGIHIFKGJLSXRQVRPSQYQVTUOUVXRXRQUVPZZO
ZNWPTWPOWPSUVTUOYOSYSVRSWPVSILCDBBADACCFKMJFEHDACJJJELCE
OUSPRSOYPTNWWVQPTXRPWORYRQVVFDCCJIFBFCBLJJFKJAGEKMHGBFKJ
WYUNRVYYRTZNWNYVVZPQVNPPTZWPKLHHGKAKJLCMGACKMDDIIHGJEDMB
SPUPQYQRZSTPQNSYQVOSNWQQXYXQJDBHMLCJLLLKFFJBHIGKKGEICCCF
ZXUVZWWWVXWOUYQUROWSQQSWTOOZDALBFAJEMLJHGILIECCDIGJMDEFJ
SQQSPVUVYXSPVSZNNZZYZRUPZWZUMEJBLCCMELFEGDAKLLBJDGMBJAJA
QWXYPNRXTOPWXUNRZRPTYQRYSNSVHEFJMIFMMLCLADBIIFMJELEBDKID
NRUXYUXPVUVUUQPSZRVXXPTOOXPPJBJCCFABFFJKCIKELHDMHHFLIHFL
YYRXQQRWXUZPYNXQRPQUWNOOPSQTCMAEAKCHFHHIELJCECDIFCKBIGGJ
WQOQOUTTZUZSRXNSTNTRQSXVSRYRAICJKKFDHGIELFGMJDDJKJFGKEBH
SVQRXTRXWZTYTYUXVZZPNZWXXVYVGIKMJIHAFFJAHKDIBMDLGGEGEELB
TVOQWYPTNUQRQYQTFWWRRSOVOOQXLDCCLMIGGFHIAAHHDLDICMFGBKHG
WTPRZTUOTORZZNWPPVNOWWOOOYSYFEGAGLFLFBMJMBBFAIJEFFBCEAMC
ZXZVXNNUOPQSXNRZZYXVRWZUPWRNJCAIJJFKGFMFBAFHCEHEEDCLBIKC
OPZUSYOORQWZPRVTOQNNZNUPOYQSMFEDIGLKLDBJJMHJJMLGDDDAABAE
YYNSQWZUUNXTXSZYORNYYNZWWPVQLBJJHHJJLELJLAKMCAJEJBMGCKBC
OXUZSYVONVXZXQQYQTVTRYTNNRNYEGMEAEEKKDAMHGEJDACGBKIMLHMK
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Figure 2.3 Texture Requiring Secondary Analysis

[Haralick, et al., 1973]. These features (or components of perception) can be given the names:

1. spectral,
2. textural, and
3. contextual.

Spectral features describe the average tonal differences of regions within an image. Each region has some average shade of grey. The textural features contain information on the spatial distribution of the tonal changes, i.e., a group of shade variations. Contextual features provide information obtained from those areas of the image surrounding the region being actively looked at and may be either spectral or textural in nature. It should be noted that colour can also be incorporated in these features. In this case, reference is to average colour differences and groups of colour variations.

2.3 Texture as an Aid to Perception

The discussion so far has indicated that there are three major elements of perception which are processed on two different levels. The element of most concern here is textural. But before going into texture in more detail it is relevant to ask what good is texture, i.e., how does it help perception?

It is known that people use texture in a number of ways when analysing scenes. Texture can be used to identify

regions as well as the similarity of different areas containing similar textures. Texture can also be used to determine boundaries separating regions. The regions may possess different textures or one region may be textured while the other is not. A uniform area can be thought of as an extreme form of texture where the repeated pattern consists of only one pixel. In addition to the above, texture may be used as a depth cue. The coarseness and size of component structures in a texture depends on the distance the texture is viewed from, a texture appearing coarser when viewed close up and finer when viewed farther away. Texture can also be used to determine some characteristics of the surface of a region. A rough surface usually provides a much different texture than a smooth one.

2.4 Qualities Perceived in Texture

It is now appropriate to focus more deeply on texture itself. How is texture perceived and what in texture is important for the percieving process? Texture clues add an extra dimension when analysing scenes and help to clarify ambiguous scenes. These clues can provide a sense of depth to a scene [Pickett, 1970]. Depending on the size and density of textural elements, an impression of surface slant may be present, i.e., a coarser texture becoming finer with distance. Regular appearing textures give a stronger impression of slant than irregular ones. When using dot

textures,[4] the perceived slant decreases as the density is increased, if large dots are used. With small dots the perceived slant increases as density is increased. The distortion of element shapes can lead to the impression of curved surfaces. The distortion of rectangular shapes produces a greater curved effect than that of circular shapes. In this case, element shape may be more important than the size or spacing of individual elements. The perception of textural elements may be enhanced by the fact that they are spatially repeated, causing the same cortical units, which respond to orientation of lines, to be stimulated repeatedly.

People, looking at textured fields, seem able to sense rough differences in simple statistics of element distribution, in addition to differences in average brightness. This was determined by having subjects analyze bar patterns formed by dots such that one bar would have a greater number of dots (a greater density) than another one [Green, et al., 1959]. When differences are greater than about 20 percent, subjects are able to reliably discriminate between different fields. The quantities of the elements can be scaled and discriminated rapidly, though the actual estimate of quantity is affected by density. Observers tend

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[4] A dot texture is composed of dots spaced a certain mean distance from each other. The distance may be varied to produce textures with different densities, i.e., areas which contain a greater or lesser number of dots.

to overestimate when small elements are present and underestimate when large elements are present.

Perception of element arrangement is dependent on the individual patterns which are repeated in the picture. Arrangements are discriminated on the basis of differences in size, shape, and orientation of the clusters formed by adjacent like-shaded elements [Harcum, 1967; Julesz, 1962]. A primary or initial impression will not detect changes among non-adjacent cells, i.e., arrangements generated by third or higher order probabilities [Pickett, 1964], where an N'th-order joint probability distribution is one which specifies that N points will have a certain grey level.

2.5 Micro-Contours in Texture

The shapes or elements in a texture (these may be thought of as micro-contours) are the most important component in the structure of a texture. It is the different types of elements grouped and arranged together to form a larger whole which may be identified as being a specific texture.

2.5.1 Importance of Contours

In the literature, it is generally conceded that contours are very important in the analysis of scenes and that contour finding is an inate mechanism involving primary processing. Some evidence of this is that developing humans

(children) will initially start with line drawings and then procede to shaded drawings [Gregory, 1973]. Studies indicate that the brain represents the visual world as line drawings first and then fills in the brightness and colour information later [Anderson, 1975]. These findings are reinforced by a study which shows that the stimulation effects of contour direction and orientation (slope) are transferred from the field of one eye to another while this is not true for colour [Murch, 1972]. Thus the effects of colour come into play at a later stage in the visual process. It also seems that grey level assimilation occurs between contours and contrast discrimination when crossing contours. If an image exists with a gradual gradient change across the picture, and a lined texture is overlaid on top, then, between two lines of the texture, the grey scales will appear to be similar. One only notices a gradient change across the lines of the texture.

Very small lines or contours may be grouped and distinguished as larger contours or lines. These macro-contours are basically of two types: explicit and implicit. Explicit contours are those which are produced by readily distinguishable unbroken lines. An example of this would be the effect produced by a black square on a white background. Implicit contours are those which are produced by impression. These contours are produced when lesser shapes are grouped together, by means of global feature analysers, to create a shape with greater meaning. An example of this

would be a dotted line in which small segments are linked together to produce a larger linear contour. This is a demonstration of the gestalt psychological concept that "the whole can be greater than the sum of the parts" [Preston, 1976].

2.5.2 Grouping of Points

Much of the knowledge on texture discrimination has been determined by having human subjects analyze textures consisting of points of various brightness and in some cases colour. It has been found that discrimination of visual texture is not based on a complex statistical analysis of the points of light, but rather involves a process that takes neighbouring points of similar brightness which are then perceived as clusters or lines [Julesz, 1965].

This information on clustering was determined earlier by Julesz [1962]. He generated two fields or regions, either side by side or one embedded within the other. The pattern of the fields was specified by an N'th-order joint probability distribution. As noted before, this is the probability that N points will have a certain grey level. A first-order distribution can be used to produce an overall tone and a second-order distribution to produce fluctuations in tone. In the study, human subjects were used to discriminate between the different fields that had been generated.

It was found that people tend to group or cluster points of light by a slicing or thresholding mechanism which separates adjacent brightness levels into two broad categories of light and dark. This thresholding mechanism can be adjusted up and down, but is still dual in nature. It cannot categorize several different brightness levels at once and it cannot cluster points which are not adjacent. Julesz calls our ability to detect clusters and lines "connectivity detection".

Grouping also occurs with points of different colour, but having the same subjective brightness. In this case, adjacent points are grouped which have similar hue, which is the subjective appearance of a colour. This is not quite the wavelength, since wavelengths which are close together in certain parts of the spectrum will have the same subjective appearance or hue. Also hue depends on luminance. At very large luminances, all lights change colour and appear to have a yellowish-white hue. At low luminances, hue cannot be distinguished at all, since only rods are active in retina [Begbie, 1973]. Thus a mainly red and yellow texture is easily discriminated from a blue and green one, but a red and green texture will not be as easily discriminated from a blue and yellow texture.

Julesz also found that compressing a picture made it easier to discriminate. This may be due to the greater information content within a given visual area. Pickett

[1964], using dot textures, supported this finding. He found that as the size of a textured area increased, the accuracy of discrimination also increased as well as the time taken to identify the texture. The time element may be simply due to the larger area which the subject's eyes had to travel over. If Pickett had tried compressing his textures he might have had different results with regard to the response time for identification. Julesz concludes that our visual system using general and primitive operations, groups or clusters points and then evaluates a few of their relatively simple properties. Those groups or clusters in which the elements are closer together provide a faster response time for identification [Pickett, 1967].

2.5.3 Grouping of Element Shapes

Just as individuals group points of varying brightness, they also group the resulting shapes. These clusters and lines are grouped together by their proximity and/or similarity. Figures 2.4 and 2.5 illustrate texture elements being grouped by proximity. In the first case the shapes are being grouped into rows and in the second case into columns. An example where grouping is by similarity is shown in Figure 2.6. The A's are grouped into columns separate from the O's, which are also grouped into columns.

Basically, grouping is a function of nearness, either nearness in terms of distance or nearness in terms of being

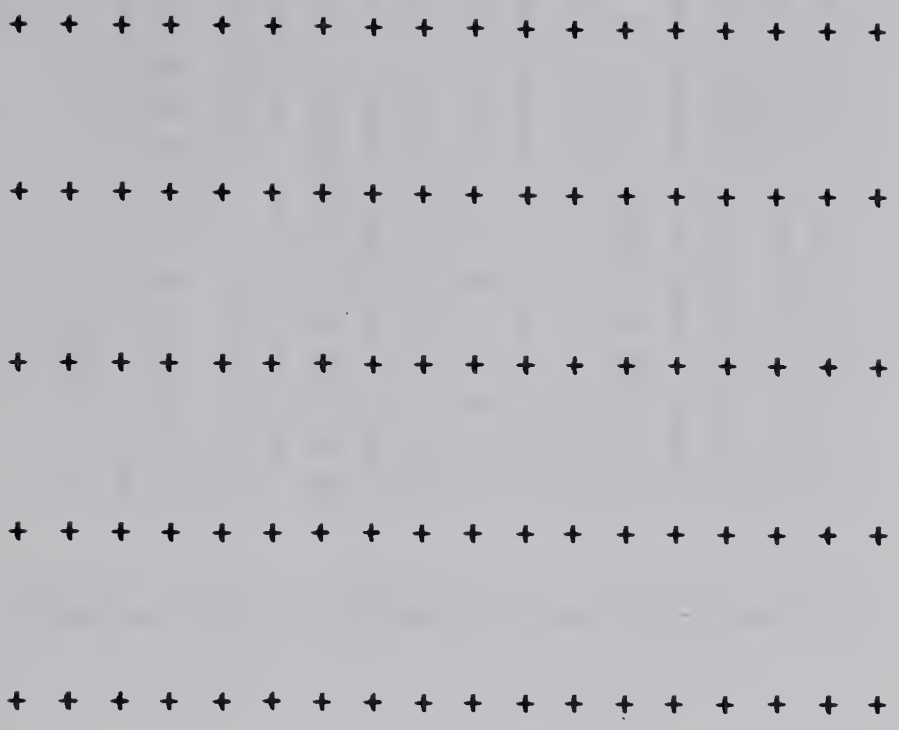

Figure 2.4 Proximity Grouping into Rows

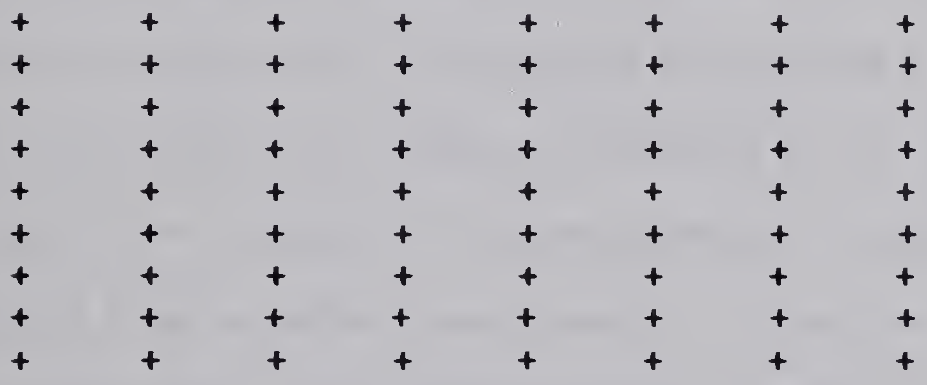

Figure 2.5 Proximity Grouping into Columns

alike. Grouping by shape can be thought of in terms of grouping by slope, length, or angle. It may also be noted that images can be grouped according to motion with items moving in a similar fashion grouped together.

Beck [1966] was able to determine that in primary processing the most important factor of grouping is the

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Figure 2.6 Grouping by Similarity

orientation of line segments. The crossing of lines is a factor, but of lesser importance. The similarity of objects did not indicate which objects would form distinct groups. These results were obtained by investigating differences in perception and grouping caused by changes in orientation and shape of two-line objects. The method involved asking observers to partition an image, consisting of three patterns, into two regions. Three patterns produce two boundaries and the observer must make a break at the more distinct of the two. The shapes used to make up the patterns were: a backward "L" shape, "T" shape, "T" shape tilted 45 degrees right, "T" shape tilted 90 degrees left, "+" shape, "X" shape, and "V" shape.

The results indicated that the orientation of a shape or figure was not a factor. Figures with lines in the same direction were grouped together. When no differences in direction were present then the crossing or intersecting of

lines produced grouping. The changing dimensions of a figure caused by rotating it is also not a great factor. Thus similarity of figure shape, which is highest for those figures with only a change in orientation, is a poor indicator of grouping.

Julesz [1962] also found evidence that line structures are important for discrimination. If the width, brightness, and orientation of lines are similar then it is very difficult to perceive diferences between regions.

Beck's results are further confirmed by Olson and Attneave [1970] who have determined that humans are able to group very well and quickly on the basis of slope and density, but poorly and slowly when angles (i.e. intersecting lines) are involved. This can easily be illustrated by looking at Figures 2.7 and 2.8 and noting how much more quickly regions can be determined in the first figure as opposed to the second one. Beck [1967] in a later work determined that brightness (degree of contrast) and slope combine in an additive manner to produce stronger grouping.

When presented with a picture which consists of two fields, one composed of circles and the other of triangles, it was found that very good and rapid grouping was accomplished. Olson and Attneave suggest that this is due not so much to the fact that the overall shapes are registered as being different, but because the slopes of the components of the shapes are different. It is the

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Figure 2.7 Slope Texture Discrimination

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Figure 2.8 Angular Texture Discrimination

orientation of the lines and components comprising a figure which are important and are so rapidly distinguishable. Olson and Attneave were not able to separate the factors of

length of line segments or texture density and slope.

2.6 Conclusion on Human Vision

It has been determined that the human visual system operates on two basic levels, one a fast parallel processing system and the other a slower serial processing system. Of these two, the parallel system appears to be the most important for texture analysis. It operates quickly to group small parts into larger parts and give a general impression. Human beings piece together spectral, textural, and contextual information when analysing and trying to understand scenes. The textural component in images is useful for both identifying and discriminating between visual regions. Individual brightness points are grouped by their adjacency and similarity of brigtness and resulting lines and contours are grouped by their proximity and similarity. The important factor of similarity is the slopes of the component line segments or contours. In general, to determine grouping, it is the specific properties of the figures which must be looked at. This leads to the conclusion that humans group on relatively simple factors and do not make use of complex statistical measures. The next chapter focuses attention on some work that has been accomplished in using computers to analyse and generate textures, and on some theoretical aspects relating to texture.

CHAPTER 3

TEXTURE AND COMPUTER VISION

It is appropriate, after discussion on how humans relate to texture, to investigate how computers have been used to analyse texture and what results have been obtained by computer analysis of texture. This discussion of texture will be confined primarily to the area of digital computing as opposed to optical or optical/digital computing which may in cases use a variety of lens, holograms, diffraction gratings, and lasers [Lendaris and Stanley, 1970; Platzer, 1976]. Optical operations are usually analog equivalents of digital processes. During the time digital computers have been used to analyse visual texture, there have, according to Hawkins [1970], been four main approaches. They are:

1. Spatial frequency count,
2. Grey-level content,
3. Local shape content, and
4. Higher order measures.

In the first case, it is known that spatial frequency is characteristic of certain patterns and that texture is strongly comprised of patterns, therefore some manner of spatial frequency count could be used to analyse textures.

One example of this approach [Rosenfeld, 1962], though not strictly digital, is where grey levels (derived from several slices through a picture) are converted into video signals and the different sized peaks tabulated and analysed in an effort to recognise different terrain types. A different non-digital example uses optics and a diffraction pattern (basically a two-dimensional Fourier transform) to process a picture, with the resultant intensity patterns used to try and classify textured scenes [Lendaris and Stanley, 1970]. Measures of this type are called gross measures since they can not separate individual spatial frequency components or differentiate phase shifts over distances. Of course other gross measures have similar problems, and depending on the circumstances, it may or may not be a hinderance.

The second approach concerns itself with grey level measures. Since grey level values and accompanying statistical properties give some idea of the characteristics present in an image, they have been used to try and describe textures. Examples of grey level measures are: average, variance, histogram, run lengths, grey level changes, grey level probability, and connected area size. These also are gross measures. The average, variance, and histogram measures are straightforward. Run lengths have to do with measuring adjacent likeness, i.e., linear similarity of grey levels. Measuring the differences between adjacent points is referred to as grey level changes. Connected area size is a measure of the size of two dimensional areas composed

of the same grey levels. Grey level probability is a measure obtained from neighbouring points. It is determined by analysing adjacent points and finding the probability that grey level 'm' follows grey level 'n' for some orientation. Thus if there exists just two grey levels 's' and 't' then in Figure 3.1 'a,b,c,d' are the number of times, for some orientation, that

- 's' follows 's',
- 't' follows 's',
- 's' follows 't', and
- 't' follows 't'.

These descriptor matrices are also known as spatial dependence matrices or grey level co-occurrence matrices.

$$\begin{array}{c|cc} & s & t \\ \hline s & a & b \\ t & c & d \end{array}$$

Figure 3.1 Two by Two Descriptor Matrix

Shape measures are an attempt to apply local filters to every point in a picture and to count the number of points which match or approximately match (given a threshold) the filter. Examples of shape measures are: edges, lines, x-shapes, circles, and wedges. Figures 3.2 and 3.3 are graphical illustrations of two of these shape measures. A problem associated with shape operators is that, while

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Figure 3.2 Line Shape Measure

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        - + -
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Figure 3.3 X-Shape Measure

operators have been used extensively for specific pattern detection [Minsky and Papert, 1969], only a small number have been tested for texture analysis and there is little idea of what different variables they should be able to respond to. At present, shape operators are not very sensitive to many characteristics of textured images.

Higher order measures compare the results of low order measures as parameters are varied. As an example, higher order measures can measure the number of points which

respond to an edge detector as a function of direction or measure lines as a function of angle and edges as a function of length, spacing, or contrast. Using measures which are dependent on other factors has potential, though deciding what to measure, how to measure it, and what the measure means remain a problem.

The rest of the chapter is concerned with specific areas where computers have been used to study visual textures. This discussion ranges from texture analysis, identification, and classification to computer texture generation. Some of the ideas presented in this initial section will be expounded on more fully when discussing these latter topics. Also some of the texture measures presented seem to correlate well with human psychological measures [Tamura, et al., 1978]. The chapter is brought to a close with a brief section on what future work remains (the unresolved problems).

3.1 Analysis/Identification/Classification

By far, the largest amount of computer-texture work has been concerned with analysis, identification, and classification. One of the main approaches used revolves around the determination and manipulation of spatial dependence matrices. When using spatial dependence matrices it is assumed that there is a uniform textured image area and that the texture information is contained in the average

spatial relationships that the grey values have with one another [Haralick, et al., 1973]. The concept of spatial dependence matrices can be used with any number of grey levels. Figure 3.4 illustrates an actual example of spatial dependence matrices. Part (a) is the original matrix of values, which is composed of the four grey levels 0, 1, 2, and 3. Parts (b) to (e) are four spatial dependence matrices derived from (a). There is one matrix for each scan orientation: horizontal (0 degrees), vertical (90 degrees), primary or left diagonal (135 degrees), and minor or right diagonal (45 degrees). It should be noted that (in this case) there is a scan in either direction for each orientation. Thus in the horizontal case, the picture element pair (2,2) is counted once when scanning left to right and once again when scanning right to left. It is also possible to generate matrices by looking at points which are not immediately adjacent but separated by distances of two, three, or more.

Deutsch and Belknap [1972] have used spatial dependency matrices in a direct manner to describe textures. They considered textures which were easily identifiable in terms of edges, edge direction, blobs, and blob size. The characteristics of a texture were determined by looking at the matrix values and their relationships to one another. For instance, if the terms of the vertical and horizontal matrices are similar to each other, then the structure of the texture elements is symmetric about the vertical and

$$\begin{array}{|cccc|}\hline 1 & 0 & 2 & 2 \\ 0 & 0 & 1 & 2 \\ 3 & 1 & 1 & 2 \\ 3 & 0 & 0 & 3 \\ \hline\end{array}$$

(a)

$$\begin{array}{c|cccc} 0° & 0 & 1 & 2 & 3 \\ \hline 0 & 4 & 2 & 1 & 2 \\ 1 & 2 & 2 & 2 & 1 \\ 2 & 1 & 2 & 2 & 0 \\ 3 & 2 & 1 & 0 & 0 \end{array} \qquad \begin{array}{c|cccc} 90° & 0 & 1 & 2 & 3 \\ \hline 0 & 2 & 4 & 0 & 1 \\ 1 & 4 & 2 & 1 & 0 \\ 2 & 0 & 1 & 4 & 1 \\ 3 & 1 & 0 & 1 & 2 \end{array}$$

(b) (c)

$$\begin{array}{c|cccc} 135° & 0 & 1 & 2 & 3 \\ \hline 0 & 0 & 5 & 0 & 1 \\ 1 & 5 & 0 & 1 & 1 \\ 2 & 0 & 1 & 2 & 0 \\ 3 & 1 & 1 & 0 & 0 \end{array} \qquad \begin{array}{c|cccc} 45° & 0 & 1 & 2 & 3 \\ \hline 0 & 2 & 1 & 2 & 1 \\ 1 & 1 & 2 & 2 & 1 \\ 2 & 2 & 2 & 0 & 0 \\ 3 & 1 & 1 & 0 & 0 \end{array}$$

(d) (e)

Figure 3.4 Example of Spatial Dependence Matrices

horizontal directions. A finer texture will produce matrices whose values are more or less similar to each other since in a finer texture there is less chance that

neighbouring grey levels equal each other. If the diagonal elements of the vertical matrix are less than that of the horizontal one, then it may be deduced that the texture is more horizontal than vertical in nature. By generating other sets of matrices with a larger separation between pairs, it is possible to gather information on the size and length of the texture elements, e.g., if the value for a pair persists in a given direction as distance is increased, then the feature which is being measured has not changed. By deriving and analysing a number of values (using different distances), a general description of a texture can be built up. This approach, though, has problems distinguishing between lighter and darker objects and between local and global structures. It also needs a uniform texture and requires some relatively high level analysis at the end.

Spatial dependence matrices can also be used in other ways. Haralick, et al. [1973] have presented a number of textural measures (statistical in nature) which may be extracted from the matrices. Characteristics of these types of measures are illustrated by the following equations.

$$F1 = \underset{i=1}{\overset{G}{\mathrm{SUM}}}\ \underset{j=1}{\overset{G}{\mathrm{SUM}}}\ (P(i,j)/R)^2,$$

$$F2 = \sum_{n=0}^{G-1} n^2 \left[\sum_{ABS(i-j)=n} (P(i,j)/R) \right],$$

$$F3 = \frac{\sum_{i=1}^{G} \sum_{j=1}^{G} [i*j*P(i,j)/R] - M(x)*M(y)}{SD(x)*SD(y)},$$

where P is the spatial dependence matrix, G is the number of grey levels, R a normalizing constant (number of pairs of resolution cells), and M(x), M(y), SD(x), SD(y) are the means and standard deviations associated with P(i,j)/R. The equation for F1 is called the angular second-moment feature. It is a measure of the homogeneity of an image. A homogeneous picture will not have very many dominant grey scale changes or transitions. As a result the matrix P will not possess many entries with large magnitude. Thus the more homogeneous an image is, the greater the tendency for F1 to be smaller.

The equation for F2 is a measure of contrast. This measure is the difference moment of the matrix P and is a measure of the amount of local variations in the image. Since ABS(i-j) is equal to n, a large entry at a high value of n indicates a large spread or high contrast. A high value for n causes n^2 to be large which forces F2 to be large.

The equation for F3 is a measure of grey scale linear dependencies. This measure is a correlation feature where

the more correlation present the larger the value achieved, i.e., if there is a constant grey tone in a direction, then a higher value is produced for the measure. Haralick, et al., suggest that when using angular dependent features for classification, the measures should not be used directly. Instead the average and range, which are invarient to rotation should be used as input to a classifier. A problem associated with some of the measures derived from spatial dependence matrices is that it is difficult to understand what they really mean. A matrix can be analysed in a great number of ways to produce a large number of different values, but are all of the values meaningful and is it possible to always understand what exactly the values are measuring (the features contain information, but exactly what information)? This possible lack of understanding should be kept in mind when generating such measures.

Related to grey level dependence matrix measures are grey level run length measures. A grey level run is a linear group of consecutive pixels all having the same value and the length of this run is the number of pixels in the run. Galloway [1975] used measures based on run lenths in trying to classify textures. Run lengths were calculated for each orientation to produce four run length matrices. The dimensions of a run length matrix are G by L, where G is the number of grey levels and L is the maximum run length. In a manner analogous to spatial dependence matrices, measures are calculated from the run length matrices. This

is illustrated by equation RF1 which produces a large value if many short runs are present.

$$RF1 = \frac{\sum_{i=1}^{G} \sum_{j=1}^{R} [P(i,j)/j^2]}{\sum_{i=1}^{G} \sum_{j=1}^{R} [P(i,j)]},$$

where P(i,j) is the (i,j)th entry in the run length matrix, G is the number of grey levels, and R is the number of different run lengths (thus the run length matrix is of dimensions G by R). By calculating and comparing several values produced by different measures or the same measure with different orientation it is possible to categorize different textured images (83 percent accuracy in classifying different terrain types).

A different method sometimes used for texture identification and classification is based on the Fourier power spectrum [Bakcsy, 1973; Weszka and Rosenfeld, 1975]. Given a picture g(x,y), where x and y vary over the image, the two-dimensional discrete Fourier transform F(n,m) is given by:

$$F(n,m) = \frac{1}{p^2} \sum_{x=0}^{p-1} \sum_{y=0}^{p-1} g(x,y)**[-2*PI*i*(x*n+y*m)/p],$$

where p is the size of the picture, PI is the mathematical pi, and i is SQRT(-1). The power spectrum P(n,m) (which is the magnitude of the complex function F(n,m)) and the phase

spectrum PHI(n,m) of F(n,m) is given by:

$$P(n,m) = [F(real)^2(n,m) + F(imag)^2(n,m)]^{**}(1/2),$$

and

$$PHI(n,m) = \arctan[F(imag)(n,m)/F(real)(n,m)],$$

where (real) and (imag) refer to the real and imaginary components of the complex functions. Certain properties of the Fourier operator can be utilized for texture analysis, e.g., it compresses data if it is (or almost is) periodic, which is one of the characteristics of texture. The power spectrum is invariant to linear translation in the spatial domain, but not to rotation. This means that the directionality of a pattern is maintained in P(n,m). If the power spectrum produces a high average value in a given narrow angular sector, then the picture probably contains contours at roughly the orientation of the angular sector. If a high average value is produced in a ring of large radius then it can be concluded that the picture is finely textured. Sometimes the power spectrum is transformed from the Cartesian system (n,m) into a polar system P(r,phi) and then manipulated for classification purposes [Bajcsy and Lieberman, 1976]. The phase function is of lesser use since it only maintains information on the location of the image window (from which the function values were generated).

A certain amount of work has also been accomplished in trying to analyse texture based on structure. Hawkins, et al., [1966], used local shape recognition and a binary

decision criteria to detect different terrain types. Masks with coefficients were applied to a picture and the values summed up, or a binary version summed and thresholded. According to a combination of values produced by different masks, textured terrain was classified. Further is the work of Tsuji and Tomita [1973] who partitioned regions in a textured scene according to properties such as shape, size, and arrangement of subpatterns. The subpatterns used were clear in outline and uniformly distributed over the region. Subpatterns were classified as atomic regions by a preprocessor and then grouped to form larger regions. Also of interest is a decision theory method by McCormick and Jayaramamurthy [1975]. Patterns of selected size, shape, and orientation were generated and then various shaped templates applied to try and analyse the resultant patterns. The application of a template to a image location was interpreted as an "event" and by means of statistical decision theory, "events" are categorized into disjoint sets. Textures or patterns are distinguished from each other by being in different sets.

Some comparisons have been carried out between different texture measures. Weszka and Rosenfeld [1976] used texture for the analysis and inspection of certain industrial materials. The purpose was to grade materials into four different classes depending on the quality of a given sample, where quality is determined by the substances surface appearance, i.e., whether it is smooth or grainy.

For identification, several features used were: the Fourier power spectra, some spatial dependence matrices statistics, and difference statistics which is concerned with the number of times that the difference between neighbouring grey levels, in one of the four principle directions, has some value 'k'. In the difference method, as in the spatial dependence method, four matrices are produced and statistics derived from them. The best results were obtained from measures based on spatial dependence matrices (slightly greater than 94 percent accuracy). Difference measures (generally comparable) were not quite as good (about 83 percent) and Fourier based measures were the poorest. An earlier study by Weszka and Rosenfeld [1975] on terrain classification produced similar results. These studies are further supported (in a terrain classification study) by Weszka, Dyer, and Rosenfeld [1976] who showed that statistics based on spatial dependence matrices and differences do equally well and better than Fourier features.

3.2 Texture Resolution and Coarseness

Texture is a two-dimensional characteristic that pertains to an area of given length and width. Thus when using many of the methods previously discussed, one would like to know how large a sample region is necessary for texture analysis to be accurate. If a sample region is too small then there will not be enough information to produce

accurate results. If a sample region is too large then there may be overlap when attempting to analyse the region, i.e., two or more textures will be measured simultaneously. In addition, texture measures are often computationally complex, another reason why using minimal sized regions, which will still provide satisfactory results, is desirable. The same problem exists when trying to find simple gradient edges. Too small an area may miss an edge while too big an area will produce edges which are not there, i.e., mistake a gradual change for an edge. A gradient edge detection approach by Hueckel [1973] uses large areas of fixed size and produces an edge-line which best fits the data. Rosenfeld and Thurston [1971] and Rosenfeld, et al. [1972] determine the average grey value over a number of different sized regions and use this information to choose a best region size to find conspicuous edges which might run through a point, where a conspicuous edge is either an isolated edge or an edge located between two large regions of significantly different average brightness.

In determining the optimal region size to measure a texture, and at the same time produce a measure of texture coarseness, there are a number of approaches that may be tried [Thompson, 1976]. One way is to look at the effect that changing region size has on results produced by classificaton procedures. Another way is to try and develop measures which respond well when the minimal size that a texture can be detected at, occurs. It may also be possible

to use the human visual system as a guide for determining the degree of textural resolution of a group of textures, i.e., using humans to classify textures as being similar or different depending on the resolutions of the textures. In addition, since texture is made up of repeated patterns, by analysing and determining the size of the basic pattern, a size for the region needed may be deduced. In this case the region will have to be large enough to contain the necessary information on the pattern and how it is repeated. Other proposed aproaches are the use of sum-of-absolute-differences where an image is compared to a shifted version of itself, the moment of inertia of the main diagonal of the spatial dependence matrix, and the amount of edge per unit area that is contained in a picture [Hayes, et al., 1974].

An often suggested approach is the use of the auto-correlation function [Rosenfeld and Troy, 1970]. The greater the fall from maximum for the auto-correlation function, the more indicative of a finer texture. A proposed way to use the auto-correlation function is for a region in an image to be compared against itself after being shifted [Thompson, 1976]. If the elements in the texture are large then relatively small shifts will give little difference in the comparison. If the elements are small then a slight shift will produce greater differences. The comparison function should be defined in terms of an angle and a shift distance along the angle. By averaging the results produced with a fixed distance and several angles,

one produces a measure which is independent of angle.

Thompson [1974, 1976] had human subjects try to determine perceived textural resolution. This was done using areas of finer texture embedded within a coarser texture. Results were compared with values produced by the auto-correlation function. The comparison gave rise to poor correspondence since humans use information from surrounding areas (contextual information) and the auto-correlation function does not.

Another approach for measuring texture coarseness is based on the average best edge size or spot size [Hayes, et al., 1974]. In this case, different sized neighbourhoods are used to detect spots. A value for each size of neighbourhood is produced and the size with largest value is chosen as best. While this approach is able to determine if one picture is coarser or finer than another, it fails to achieve a proper ratio of coarseness. Later work by Funakubo [1978] attributes this improper ratio to the fact that, in digital pictures, the correspondence between pixels of differently scaled images is not exact. As a final note, if the characteristics of the textural edges being looked for are available or the strength of the edges can be determined, then it is possible to produce an adequate value for the region size needed [Thompson, 1976].

3.3 Other Areas of Research

Besides the relevant areas of texture analysis and resolution there exist other texture problem areas where computers have been used. These consist of finding object edges in a textured field, using texture as a depth cue, and texture generation.

3.3.1 Extraction of Edges Surrounded by Texture

Sometimes it is necessary to determine and extract object edges situated in a textured field. The use of a gradient edge detector for this purpose will detect the object's edges, but it will also detect and produce a great number of what might be called spurious edges that are part of the textured field. Nevatia [1975] has presented a technique to eliminate these extraneous edges. The boundaries of an object are determined by the use of a special linking algorithm which links edges produced by a gradient edge detector. For the purposes of the linking algorithm, each edge segment e(i) has a position p(i) and direction a(i) associated with it. The algorithm breaks up the entire range of directions (360 degrees) into a number of equally sized intervals. Connected with each of the intervals is a median angle θj. Every edge element is looked at and placed into a set Ej if the direction a(i) of the edge lies within some fixed range of the direction θj. For each θj the coordinates of the picture are transformed

such that a new x-axis (X') is along θj. After coordinate transformation the image is divided into strips (called buckets) which are aligned with X'. Edges in each strip which are spatially closer than some given threshold are linked together as are segments in neighbouring strips that are very close together. All linked segments which are of length greater than some given amount are kept; the rest thrown away. At this stage it is hoped that the edges remaining are only those which belong to the object of interest.

Problems with this approach centre on the thresholds used with the angles and lengths. Specific threshold problems are the optimal angle size for intervals, the range used with the intervals when looking at the edge directions, the spacing to produce strips, and the best value for length when determining which edges to keep and which to discard.

A different approach for processing the output of a gradient edge detector and for finding well defined edges (curves) located in a noisy background is that of Rosenfeld, Lee, and Thomas [1970]. In this case, the noisy output from an edge detector is processed by a dotted curve detection mechanism which looks at the neighbourhood about each curve point. If two other curve points exist on opposite sides and within a fixed distance of the central point, then the centre curve point is retained, otherwise it is deleted. Iterating this procedure a number of times will remove many

spurious curve or edge points.

3.3.2 Texture as a Depth Clue

Very little work has been done, in image processing, using texture as a depth cue. Two individuals who have investigated this are Bajcsy and Lieberman [1976]. They looked at gradients of texture created by water and grass with the reasoning that the farther away a textured surface is viewed the finer the texture will appear. This is due to perceived shrinkage of elements or element spacing. The technique applied is based on the Fourier transform and by transforming and manipulating these values it is possible to classify the texture as well as generate numbers which are smaller where texture is finer and larger where texture is coarser. While these values do not necessarily mean that those portions of the scene are farther away or closer to the viewer, the values are useful as an extra clue when more information is needed to clarify an ambiguous scene.

3.3.3 Texture Generation

An area which has attracted some degree of interest is that of texture generation. One reason for generating texture is that artificial textures are useful in testing human perception [Rosenfeld and Lipkin, 1970]. It is possible to produce consistent textures with specific properties for controlled experiments involving humans,

e.g., the perception of patterns in noisy and cluttered pictures. Also texture generation can be used to fill holes in pictures. In transmitting a picture it is possible that a section of the received image will be missing (this can arise during the transmission of images from spacecraft or satellites) and using texture generation it may be possible to fill in missing areas with textures similar to the surrounding regions.

If a good means of texture generation exists then it may not be necessary to store a digitized textured region [McCormick and Jayaramamurthy, 1974]. It may be enough to store the parameters or characteristics that describe the texture and then produce the textured region when necessary. This means that less memory is needed to store the picture and the information stored is more compact and less redundant, which can lead to easier picture analysis.

For the most part texture generation is accomplished by repeating some pattern or subpattern many times, both horizontally and vertically. Both the properties of the subpatterns and their placement may be varied. Furthermore, subpatterns may themselves be built up from other smaller subpatterns which may also be built up from subpatterns. This multi-level process is carried out as far as desired or as far as practical to do so. The use of such a heirarchial structure for texture embedding has been implemented in a graphics system by Kunil and Arisawa [1975]. It should be

noted that it may not be possible to perceive, by viewing the resultant picture, individual subpatterns which have been combined and iterated, i.e., it is not always possible to recover the input information by analysing the output.

Subpatterns, once generated, can be placed using different methods. One way is to define a set of potential locations for the placement of subpatterns [Rosenfeld and Lipkin, 1970]. These positions can be regular in nature, random, or dependent on previous locations. At each of the locations a deterministic or probabilistic decision is made whether to place a subpattern or not. This decision can also depend on previous decisions, i.e., it can depend on the relative positions of already placed subpatterns. A simple case of using previous decisions is having a limit indicating when to stop. Once subpatterns are placed, they may be rearranged. This can be accomplished by spreading them apart, drawing them together, distorting them to produce a curved effect, or permutating them. Different placement plans will not necessarily yield different results. If the placement location is random and each placement decision is independent of each other placement decision, then the result will appear the same whether the placement decision is deterministic or probabilistic. In generating textured images it might be necessary to store a large number of different subpatterns to draw from. This is because there is such a variety of natural textures. Subpatterns could possess different properties (some of

which may be interdependent) which may be varied. Subpatterns are then produced by specifying a set of property values. Some of these properties, like grey level, are easy to define while others, like shape, are not as easy.

So far the majority of texture generation has consisted of producing scenes which possess certain statistical properties for use in visual perception experiments. Examples of this are [Gibson, 1950; Julesz, 1965; Pickett, 1964]. There has been some work though in producing natural looking textures. Rosenfeld and Lipkin [1970] have looked at this area using the ideas discussed in the preceeding paragraphs. As well, interpolation is used for filling in small gaps in natural textures. This is done to remove edge effects produced when juxtaposing similar textures. Conroy [1969] simulated natural textures by drawing "signs". A sign being any collection of lines, usually spatially close to one another. Examples of signs are circle, squiggle, hatch (a cluster of short line segments), and square. Using a small number of basic signs or classes of signs different textures are produced. Conroy's process involves mapping a curved surface into planar regions; distributing one or more signs on the regions or portions of the regions, where signs are distributed randomly and each sign has associated with it a size, density, and orientation; finally performing an inverse mapping to produce the original surface. Through a trial and error process this technique can produce natural

looking textures.

A more automatic scheme is that of McCormick and Jayaramamurthy [1974]. Closely related to this is that of Tou, Kao, and Chang [1976]. Here picture elements of a two-dimensional textured scene are viewed as a two-way seasonal time series where the length of the season is the length of the picture row. The process basically involves using seasonal time series techniques to analyse a "parent" natural texture to obtain parameters, and then using the parameters and further seasonal time series methods to synthesize a similar appearing texture.

3.3.4 A Theoretical Basis of Texture

As mentioned earlier, many texture generation schemes repeat basic patterns. Based on this idea, Zucker [1976] has proposed a theoretical basis for texture in which there exists three entities called:

1. primitives,
2. ideal textures and,
3. observable textures.

Primitives are combined and recombined to form ideal textures. These ideal textures are transformed to produce observable textures. Primitives may be simple in form such as a box or cross and locations where primitives can be combined are called active sites. The side of a box or the endpoint of a line making a cross can be considered active

sites. Primitives which produce different effects in different groupings and can be grouped different ways are called "multistable". A simple nondescript local cue can, when grouped, force visually recognizable global organization. Ideal textures produced are not observable, but are underlying structures whose vertices and points are represented by a graph. This ideal graph is transformed to produce a graph which represents the observable surface texture.

The results produced by transformations can be classified into three catagories:

1. Gradient - the physical transformations such as rotation.
2. Perceptual - a transformation to relate a given pattern to a certain singular pattern.
3. Modeling - transformations to produce a class of patterns (e.g. wood).

On the whole, these classifications are poor. Their generality produces a certain ambiguity. It may be necessary to have restrictions on transformations, e.g., a transformation must not destroy a graph since this would allow for no inverse transformation. Also models produced should be consistent with our visual system so that what is produced is recognizable. If different internal textures can be operated upon by several different transformations to produce the same observable texture then the texture produced is said to be syntactically ambiguous. This may

not necessarily be visually ambiguous. A texture that contains folds, which cannot be determined as being visually into the surface or out of the surface, would be visually ambiguous.

3.4 Summary on Computers and Texture

It has been seen that approaches to texture can be segregated into four main categories. These categories include measures based on the Fourier transform, spatial dependence matrices, run lenths, differences, and shapes to name some of the more popular approaches. Certain approaches (e.g., spatial dependence matrices) have achieved good results in classifying different types of terrain and materials. Other aspects are concerned with determining texture resolution (how large an area should be looked at when analysing a texture), extraction of edges located in a textured field, how texture might be used as a depth cue, and texture generation where texture is created, for the most part, by the repeated placement of patterns. Related to texture generation was a theoretical outline for texture.

3.5 Further Work - Unresolved Problems

There are still many problems associated with texture analysis and the measures which are used. With spatial dependence matrices, work can be done on grey tone normalization or on producing features which are invarient

under monotonic grey tone transformations (since a given texture can be perceived as being lighter or darker by different individuals or devices and texture is to some extent independent of tone).

Also texture coarseness should be further looked at. This could provide easy methods for determining region size. The distance between picture element pairs used in defining spatial dependence matrices needs to be determined in a good manner (this distance is dependent on resolution).

In the area of texture generation, work needs to be done on the generation of realistic appearing textures, i.e., being able to generate an arbitrary natural appearing texture as well as to imitate natural textures. There is also 3-dimensional texture generation. Problems here involve the creation and placement of 3-dimensional subpatterns, how to produce highlights and shadows, and the use of distance to produce patterns either blurred or clearly in focus. The 3-dimensional textures would have 2-dimensional output analogous to the 3-dimensional graphics situation.

There is also work to be accomplished in detecting and extracting shapes. What exactly, for instance, should be looked for when analysing shapes, In addition, how should different measures be combined to obtain higher order functions which are effective. Further research also needs to be done on image descriptive languages which describe

image components and their relationship. Some work has been accomplished in this area by Pfaltz [1972] and more specifically by Carlucci [1972].

CHAPTER 4

SECOND-ORDER PICTURES AND BOUNDARY DETERMINATION

Discussion now proceeds to the generation and application of 2nd-order pictures to textural boundary determination. Included is a look at what measures are used and how they can be applied to produce 2nd-order pictures which can be subsequently processed by procedures such as smoothing, thresholding, edge detection, and merging. In addition, what data is used and how the data is manipulated is presented.

Compared to gradient edge detection little work has been done on determining textural boundaries. Rosenfeld and Thurston [1971] were able to generate edges between certain textured regions if the regions differed enough in average brightness. These edges, as noted earlier, were called "conspicuous" edges. A structured approach using decision theory was proposed by McCormick and Jayaramamurthy [1975]. Textured regions which have been generated using certain patterns are analysed using a decision theory method. Known patterns are looked for and if found classified. A pattern which cannot be classified into one of the known sets is

assumed to be on a border. The reasoning is that an unkown pattern is composed of parts of patterns from adjacent regions with the result that it is different from the patterns wholly within the regions. A different approach by Thompson [1977] uses a textural edge operator analogous to the modified Robert's cross operator, which is given by

$$R(i,j) = ABS[p(i,j) - p(i+1,j+1)] + ABS[p(i+1,j) - p(i,j+1)],$$

where p is a matrix of picture elements. At certain intervals in a scene, the four quadrants of a square are looked at and statistics based on (for example) spatial dependence matrices determined. The difference between the values in the upper-left and lower-right quadrants is added to the difference between the upper-right and lower-left quadrants. If the summed value is large enough, then a textural edge is said to exist.

Recent work by Deguchi and Morishita [1978] on image partitioning of textured scenes can also be used to find textural boundaries. This approach uses weighted coefficients to obtain a weighted sum of the grey levels in the neighbourhood surrounding a picture element. The coefficients are initially determined by analysing sample textures. Looking at the neighbourhood about each point and using the weighted coefficients, weighted sum values are produced and then combined using a region growing technique.

When a region being partitioned stops growing, the boundaries are said to have been found. Related to partitioning and region growing are results produced by Pavlidis and Tanimoto [1975]. They generate a well-defined artificial textured picture with known characteristics, and then recursively divide the picture up into 4, 16, 64, etc., parts. Each part is measured and similar parts combined. A part that is not uniform is further subdivided. If regions can be found then the boundaries may be determined. Problems associated with this are in determining whether a region is uniform, whether different regions are similar, what techniques should be used in measuring a region, and how far regions may be subdivided until textural measuring is impractical. Additional information on image segmentation or partitioning techniques may be found in [Sklansky, 1978].

Discussion now centres on the work accomplished in this thesis. Presented in the discussion are direct texture measures that require no training samples. These measures can be used to generate 2nd-order pictures which upon manipulation can be used to determine textural boundaries.

4.1 Texture Measures

In deciding what texture measures should be used certain criteria were followed. First, the measures should be few in number and relatively simple, since they will be

applied to a neighbourhood about each and every point in a picture. Second, the measures should be direct, i.e., obtainable directly from the picture elements. This direct measuring is in contrast to measures based on spatial dependence matrices (for example). Third, the measures should be orientation dependent. Thus information on directionality may be determined. Forth, the measures should attempt to determine inherent characteristics in a texture, and should not require training samples to be effective. By employing these four rules as a guide, two measures were defined to produce values from a linear vector of points. In discussing the measures let P be the set of n points to be analysed and D the set of n-1 adjacent differences. Thus

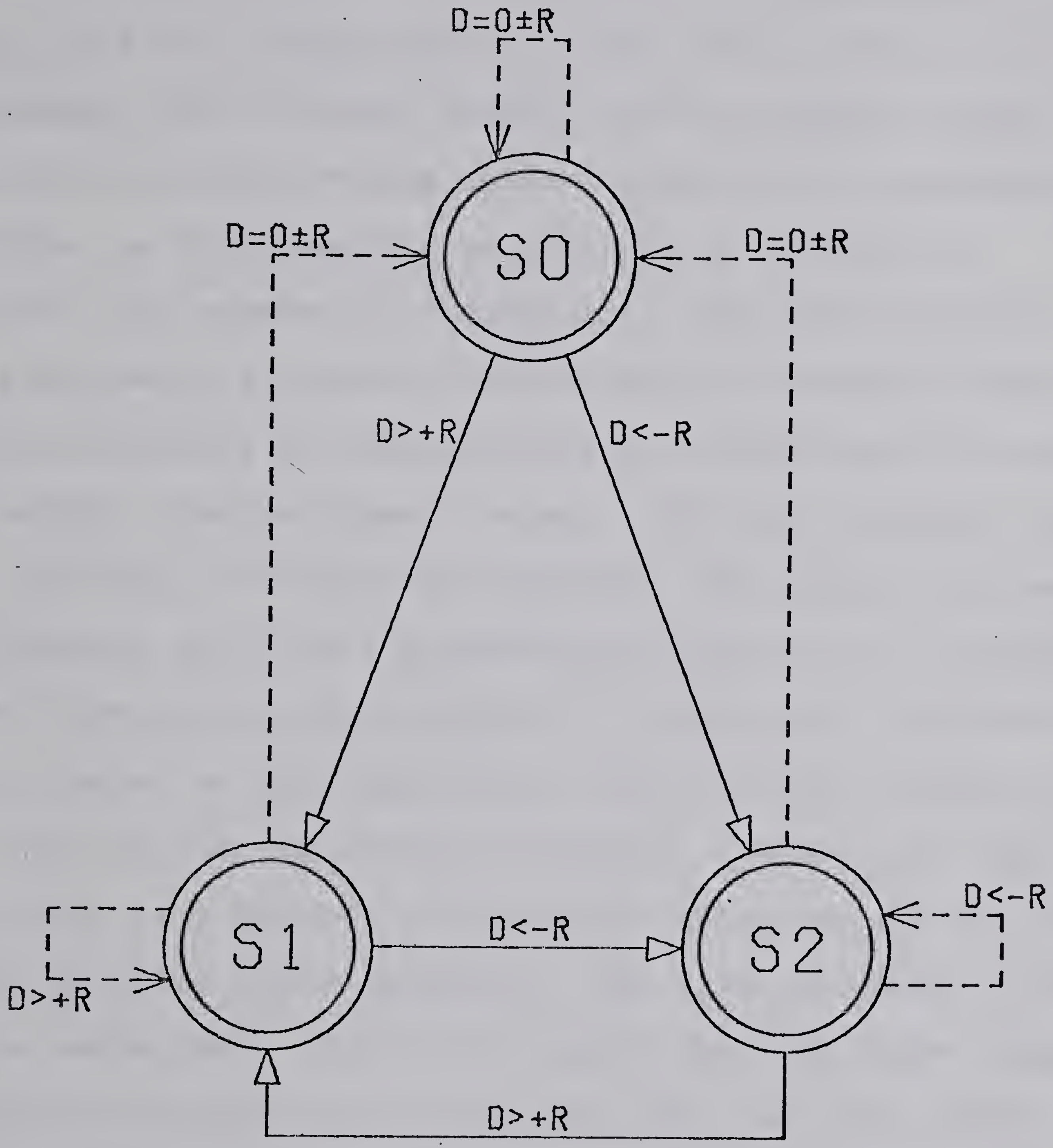
$$P = p(1),\ p(2),\ \ldots,\ p(n),$$

and

$$D = d(1),\ d(2),\ \ldots,\ d(n-1),$$

$$\text{where } d(i) = p(i) - p(i+1).$$

The first measure determines frequency characteristics pertaining to texture. It is described by the finite state machine (FSM) shown in Figure 4.1. A counter is initially set to zero. For each $d(i)$, $i = 1, 2, \ldots, n-1$, if $d(i) = 0 \pm R$, a change of state occurs, but the counter remains unchanged. The quantity R, which is user specified, is a fluctuation threshold and possesses a value such as 0,



S0 is the starting state.
Solid lines and arrows indicate state change and count increment.
Broken lines indicate state change only.

Figure 4.1 FSM Describing First Measure

1, 2. Differences less than or equal to R are treated as zero. If d(i) is greater than +R or less than -R then a change of state occurs and the counter is incremented. This change of state process has the effect that, whenever the difference (rise or fall) between picture element values changes, by a great enough amount, from zero to negative or positive, or from negative to positive or positive to negative, the counter is incremented. The value produced by the first measure contains information on frequency since texture frequency is characterised by a repetition of rising and falling picture element values. The more frequent the rise and fall, the finer the texture. The amount R is used to eliminate very minor fluctuations appearing in a texture. These fluctuations may naturally be present in a texture or be introduced by the digitization process (this problem is discussed further in the next chapter). Either way, they contribute very little to the texture structure and can be viewed as noise during analysis. The value produced by the FSM is normalized. This is to insure that the value always falls in the range 0 to 63 and also that the final value produced is to some extent independent of the number of points looked at, i.e., a dozen points of a fine texture will have the same expected value as two dozen points of the same texture. Thus if UF is the unormalized value, then the final value F is given by

$$F = (UF*63)/(n-1).$$

This result is rounded off to produce an integer pixel value.

The second measure captures information on contrast in a texture. This measure is defined as

$$C = UC/(n-1),$$

where UC, the unormalized value is given by

$$UC = \sum_{i=1}^{n-1} \mathrm{ABS}[d(i)].$$

Thus value C is the mean of the absolute differences between adjacent points. A high contrast picture will have larger differences than a low contrast picture and therefore will tend to produce a higher value. The measure is also dependent on the coarseness of a texture. A coarse texture with large elements will tend to produce a low value since the majority of points are contained in the element body and the element is fairly uniform in grey tone.

These two measures are used to analyse four vectors about each point in a textured scene, where one vector exists for each orientation: horizontal (0°), right diagonal (45°), vertical (90°), and left diagonal (135°). The four vectors can be situated symmetrically about a point of interest making a star shape with the given point in the centre. This is illustrated in Figure 4.2. If the point p and its neighbourhood lies totally in either one region or

```
*   *   *
 *  *  *
  * * *
   ***
****p****
   ***
  * * *
 *  *  *
*   *   *
```

Figure 4.2 Symmetric Star Neighbourhood

another then this is a satisfactory approach, but if p is near a region boundary then the measures will produce incorrect values since areas containing different texture will be measured simultaneously. A different approach is to measure the elements on either side of p and choose one of the two values produced as representative of p. Further it may not always be necessary to analyse points on both sides of p.

For each orientation, the texture is scanned in one direction and it is possible to use some of the previous values calculated in determining the present value of p. Thus scanning horizontally from left to right, if the value calculated from neighbouring points immediately to the right of p is significantly different from the previous values of p then it can be deduced that a different texture has been encountered and the measure is looking at two different textures to calculate a value. In this case, the value from the points left of p should be determined and used. The

left side of p should continue to be used for determining values until a significant enough change has occurred indicating that a different region has been encountered. This would cause the right side to be used again. In controlling this switching mechanism the unormalized values UF and UC are used. Thresholds indicating the amount of change before switching can be specified, as well as a delay which inhibits switching for a length of time (distance). This is to help prevent the vector switching mechanism from oscillating when very irregular textures are being analysed.

Since several points on one of two sides of a location are being analysed, a certain amount of spatial "freedom" is required. Along the sides and corners of a picture this condition will not, depending on the orientation, be present. As a matter of fact, it is possible to think of a picture as containing nine regions which may require different processing, the regions being the 4 corners, 4 strips, one along each side of the picture and between two corners, and a large central portion. While it may not be necessary to process the side and corner regions, some effort nonetheless should be made to do so. It was decided that when a point p was close enough to a picture edge such that the vector switching mechanism could not function then the mechanism is locked or inhibited with the vector pointing away from the edge being approached.

In the case of the diagonal orientations, two corners

cannot be fully approached for each orientation, e.g., in the left diagonal case, scanning cannot fully approach the bottom-left and top-right corners since the size of the neighbourhood being measured exceeds the diagonal width of the corner portion being looked at. Thus, given that the corner is an M by M square, the measure obtained from the diagonal of this square is used to represent the entire corner. This can, in some instances, lead to an erroneous value for the area since the diagonal may not be representative of the entire corner. Correction for this can be done at a later stage by analysing values produced outside the corner region. If all the outside values are different from the inside value, the inside value is changed accordingly.

Two values are produced for each of the four orientations. This leads to eight values, each value considered as part of a 2nd-order picture. What now follows is a discussion explaining how the 2nd-order pictures are manipulated to produce a final result (the textural boundaries).

4.2 Manipulation of Second-Order Pictures

Two different sets of test data were used to produce 2nd-order pictures. One set consisted of artificially generated textures and the other set of natural textures. These data sets are discussed more fully in the latter

portions of this chapter. Due to the regular nature of the artificial texture set, slightly less manipulation was required to produce final results. Sets of 2nd-order pictures and sets of processed 2nd-order pictures are, in the following discussion, also referred to as component pictures.

Second-order pictures are initially processed by a smoothing operator (using program PSM3 as described in the Appendix). One reason for doing this is that analysis of very irregular textured images will for some locations produce values different from the majority in a textured region. Smoothing helps to even out these fluctuations. Another reason is when small textured areas are close together it becomes impossible to measure only one region at a time, i.e., the neighbourhood being analysed extends over multiple regions. Smoothing can reduce the effects of this multiple measuring. The amount of smoothing required depends on the amount of fluctuations present in the 2nd-order pictures. For the artificial texture test set, a 3 by 3 square smoothing operator was applied to each point. This operator assigns to each location the average value of nine points (centre point and eight immediate neighbours). For the natural texture set, being more irregular, a larger and different shaped neighbourhood is used. This is a 10 by 10 symmetric star shaped neighbourhood. A total of 41 points are thus involved in calculating a mean value (centre point, 5 points above, below, left, right, and 5 points in each of

the top-left, top-right, bottom-left, and bottom-right diagonals). The star shaped neighbourhood is used since it requires fewer points than a square neighbourhood (41 versus 100) and is still able to produce satisfactory results.

After smoothing, the set of pictures derived from the artificial textures are processed by an edge detector and merged together to produce a single final picture. Since the purpose of this thesis is not to develop a better gradient edge detection mechanism, a rather straightforward approach is used. The algorithm (program PED) looks at a rectangular neighbourhood around each point in a picture. The maximum and minimum element in a neighbourhood is found and if (MAX-MIN) is greater than or equal to some threshold an edge point is said to exist. A 3 by 3 square neighbourhood is used, and the threshold value is determined by visually analysing the histograms of smoothed second-order pictures and noting the distribution of grey levels. As a rule of thumb, the larger the spread of the grey levels the larger the value of the threshold which can be specified. A balance must be struck when determining a threshold. If too small a value is chosen, then minor variations in grey level may be mistaken for edges and edges which are produced can be very coarse. If too large a threshold is chosen then edges may be missed entirely. The output of the program is in the form of a binary picture consisting of 0's and 1's, where a 1 represents an edge point.

Once a number of component binary edge pictures have been created they are logically OR'ed together (using program PCAT) to produce the final resultant edge picture. One reason for doing this is that no edges will be lost, even if they occur in only one component edge picture. A very clear edge may be present in one or two of the components, but be entirely missing from the other components, e.g., a boundary can be very distinct when scanning a textured picture in the horizontal direction, but be faint or nonexistant when scanning in the vertical and both diagonal directions. A combination of logically OR'ing and AND'ing of the edge components can probably produce the best results, but the problem is which components should be AND'ed and which OR'ed? Every set of components would have to have its own personalized set of logical operators, which a human agent would have to specify. This results in human analysis rather than computer analysis of image data. Whenever practical, it is desirable to remove the human element and provide a system which is as automatic as possible.

A different way to combine binary pictures is by using a threshold value where an edge point is produced, for a spatial location, if N or more input edge points exist. It is possible, in cases, to use this as a measure of the strength of an edge [Nevatia, 1976]. This procedure can be useful if some initial processing is to be applied only to

those edges which are present in all components. Also an edge can be output if it is present in any component and then characterized depending on which component it is present in. The problem with such an approach is that a threshold must be determined. Except in the cases where the threshold N equals 1 or the maximum possible, determining the threshold may not be easy or meaningful. If given seven component edge pictures and two resultant edge pictures derived with a threshold of 3 and 4 respectively, then it can be said that the picture created using a threshold of 4 possesses stronger edges than the picture using a threshold of 3. But how is one picture more useful than the other? Also, as mentioned, an edge may be clearly present in one component picture and totally missing from the rest and the use of a threshold value may overlook this fact. It should be noted that for a threshold equal to 1, the result is equivalent to logically OR'ing all edge component pictures together and for a threshold equal the maximum possible, the result is the same as logically AND'ing all component pictures.

To summarize, a slight smoothing is performed on the 2nd-order pictures produced from artificial texture test pictures, then edges are extracted from the smoothed pictures, and finally the edges are combined to produce a final boundary picture. Since edges are extracted before the component pictures are combined, the final resultant picture will have more than one boundary in some locations

(as shown in the next chapter). If this is undesirable, it can be eliminated by combining the component pictures before extracting edges, as is done with the natural texture data set. In this case, the resultant picture was left as is, to illustrate how edges are produced in various locations depending on the scanning orientation.

Manipulation of the natural texture data is, due to its irregularity, slightly more involved. After smoothing is performed, the component pictures are thresholded to produce binary pictures. The prior smoothing process helps to produce more uniform regions when thresholding. An alternative to smoothing could be an iterative histogram modification technique where peaks in a histogram are accentuated such that the modified image consists of regions whose grey levels correspond to the original peaks [Rosenfeld and Davis, 1978]. This image can then be easily thresholded. The effect of thresholding is to produce distinct regions and since these regions consist of binary values, the various component pictures can be immediately OR'ed together to create a single picture.

Thresholds, to produce binary pictures, are determined by examining the appropriate histograms and noticing where two peaks indicating two major regions, occur. A similar approach has been used by Davis, et al. [1975] and more information on the selecting of thresholds may be found in [Weszka, 1978]. In this case, an intermediate value is

chosen in a manner which can be automated, i.e., the first value which starts to significantly increase leading to the second peak in the histogram. A picture histogram which does not have two noticable peaks is indicative of poor separation between regions in the picture. If one of the two 2nd-order pictures produced for an orientation has good picture histogram separation, while the other does not, then using the good histogram, a threshold value can be determined for the poor histogram. This is accomplished by picking a threshold which will break the poor histogram into two parts, approximately the same size as the two parts specified when picking a threshold for the good histogram. If both 2nd-order pictures for an orientation have picture histograms with poor separation or no distinguishable peaks, then these pictures are ignored as far as further processing is concerned. Pictures produced by the thresholding process, which are to be logically OR'ed together, should have backgrounds with a similar logical value to ensure that, in general, 0 will be OR'ed with 0 and 1 with 1. If a picture has a background different from the majority, then it should be inverted before or during the OR'ing process (0 to 1 and 1 to 0). The combined picture is now smoothed by a 3 by 3 square operator to remove any pixels which are entirely or mainly surrounded by different valued pixels, i.e., a pixel of value 1 surrounded by 0's. This may be thought of as a noise removal process. The edges are now extracted to produce a final boundary picture using program

PED with a 3 by 3 square operator and a threshold equal to 1.

4.3 Picture Test Data

Prior to discussing the results, it is important to review where the test data originated from and how it was handled to create suitable test pictures. As mentioned earlier, two different types or sets of test data are used. One set consists of pictures comprised of adjacent textures which have been artificially generated. These textures are visually easily identifiable as well as being regular in nature. The other set consists of pictures composed of adjacent natural textures. These are not nearly as recognizable or regular in structure. Artificial textures are used since they provide a controlled test environment. Picture characteristics are known, as well as what results should be produced. This allows accurate monitoring of program functions and the processing of textures with specific properties. Natural textures, though, are of importance since they originate from the "real" world and thus are more significant in scene analysis. Their irregular makeup provides a greater degree of difficulty for analysis. The subsections that now follow explain where the basic test data originates from and how it is manipulated to provide final test data.

4.3.1 Sources of Picture Data

In order to test ideas, theories, and resultant programs it is necessary to produce initial picture data. For the artificial test set, textures were generated using a program called PMGEN. This program takes a user specified rectangle (pattern) of grey levels and repeats it N times down and M times across to produce a textured image. As an illustration, if the 1 by 2 pattern (0 1) is repeated 256 times down and 128 times across, the result is a 256 by 256 pixel image consisting of vertical lines (the value of the lines alternating between 0 and 1).

Textured pictures for the natural texture test set were obtained by directly digitizing textured materials such as sandpaper, roofing shingle, etc. A series of photographic plates collected in a book by Brodatz [1966] was considered, but not used since the photographs produced poorer quality digitized images than actual substances. It was necessary to digitize materials at different scales, orientations, and lighting conditions. Later, using subjective decisions, those digitized pictures which most accurately represented the original materials were select for test purposes. Some problems encountered when digitizing a scene involved obtaining high enough resolution and achieving balanced lighting. In some cases, a scene had to be illuminated in such a way as to compensate for uneven light absorbtion characteristics of the television camera lens.

4.3.2 Manipulation of Basic Picture Data

Once a group of basic textured images are produced, it is necessary to manipulate the pictures to form actual test data. This may initially involve performing a linear transformation (using PTRAN) on a picture to lighten it, darken it, or increase the contrast. A picture can be transposed (using PTRP) to change the orientation or reduced in size (using PRED) to create a finer texture. The program PWIN can be used to window out sections of interest and PCAT used to concatenate regions (to create a larger picture).

Once two suitably textured pictures have been produced, it is necessary to combine them to create a final picture which has different textured regions adjacent to one another. The program PCAT can be used for this purpose, though it is limited to handling regions specified as rectangles. When combining two different textured pictures it is desirable to have regions of various shapes and sizes. A practical means of accomplishing this is by using a binary mask which controls the merging of the two pictures. The value of a element in the mask indicates which of two pictures is to be looked at (0 for one picture, 1 for the other picture) and the location of the element in the mask specifies the location of the picture element (in the picture looked at) which is to be output. If the mask has a region composed of 1's while the rest of the picture is 0's, then when combining two pictures with the mask as control, a

picture is produced with a region of similar shape to the mask, from one picture embedded in the material of the other picture. This is illustrated in Figure's 4.3, 4.4, 4.5, and 4.6. The first figure specifies a mask, the next two figures are the two regions which are to be combined and the fourth figure is the result of combining these two figures with the mask as a control.

A mask may be produced in one of two ways. It can be specified mathematically or it can be derived from another picture. In the first case, a figure is mathematically specified (e.g., a rectangle or a circle) with some given dimensions at some location in a blank picture. A blank picture is one whose elements all have the same value. If the blank picture is composed of 0's then the figure can be indicated by 1's. The problem with this approach is that it may not be very easy to specify a complicated figure or it may require the overlapping of several figures to achieve the desired results. The second approach takes a picture which primarily consists of very light and dark regions, and using a threshold value, maps the elements to either 0 or 1 depending on whether the element value is less than the threshold or greater than or equal to the threshold (the program PMGEN can accomplish this). The mask will have the same region configuration as the original picture. By having a dark or light circular, rectangular, or any other shaped region on an appropriately light or dark shaded background any type of mask can be produced. A simple way

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Figure 4.3 Mask Picture

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Figure 4.4 First Picture to be Combined

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Figure 4.5 Second Picture to be Combined

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Figure 4.6 Resultant Combined Picture

to produce a mask is to place desired shapes of dark material on a light background, digitize the result, and then threshold it. It may be that after the digitization and thresholding process, stray elements will exist in the mask. These stray elements are totally or almost totally surrounded by opposite valued elements, e.g., a 0 valued element surrounded by 1 valued elements. It is possible to clean up or eliminate stray elements using program PSM3. This will cause the central element to be changed to whatever value the majority of its immediate neighbours possess. Program PSM1 may also be used. This program scans the centre element and four neighbours (above, below, right, and left) and if the central point is surrounded by three or four opposite valued elements then the central point is assigned the opposite value. Thus a zero valued element bounded by three or four one valued elements would be assigned a value of one. The converse is true for a one valued element bounded by zero valued elements.

In generating textured test pictures, masks are chosen which provide a variety of different shapes and different sizes of textured regions. This allows for diverse test conditions to be present, e.g., a few large regions, large regions separated by small regions, a number of small regions close together, small regions far apart, etc. In addition, boundaries of regions can be composed of straight lines with different orientations and also curved lines, where the curve is either positive or negative depending on

the relative position of adjacent regions.

Discussion continues, in the next chapter, with a presentation and analysis of the results. These results, both pictorial and tabular, are segregated into two groups according to whether they are derived from artificial or natural textures.

CHAPTER 5

RESULTS

In this chapter the pictorial and tabular results produced by processing artificial and natural texture test sets, where each test picture contains two different textures, is presented. The artificial test set is given first, followed by the results obtained from the natural test set. Actual test pictures are shown and when referred to in the discussion, *background* is used to indicate whatever type texture occurs in the upper-left corner of a picture and *foreground* to the other type texture occuring in the picture. Tables of texture characteristics are presented to help give the reader some idea of just how different the background and foreground textures are. In some cases, a sample of 2nd-order pictures, that have been generated, is given and in all cases tables of 2nd-order values which indicate qualities pertaining to the values produced, is given. A final boundary picture is shown and a boundary comparison table produced to indicate how well the boundaries match the ideal, or best boundary possible. In some cases, the boundary picture is overlaid on the original test picture to provide a direct visual indication of the

position of the derived boundaries relative to the textured regions.

5.1 Tables

Three types of tables are given. The first, a texture characteristics table, is used to show some of the characteristics possessed by the two textures occuring in a test picture. In this table a descriptive name is assigned to each texture and the mean and standard deviation (S.D.) is calculated from the values produced for each texture by the two measures (F and C) described in the previous chapter. These values are followed by four groups of five statistical measures determined from the four spatial dependence matrices (one for each orientation). The matrices are specified using a separation of 1 between picture element pairs and are derived from the two textures which make up a test picture. The five statistics used are obtained from Zobrist and Thompson [1975] and used by Thompson [1977] in his texture boundary analysis work. The inclusion of values produced by these measures is also meant to give the reader some idea of the type and range of numbers that such statistics can generate. The five measures are defined as follows:

$$T1 = (1/R) * \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} i*j*P(i,j),$$

$$T2 = (1/R) * \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 * P(i,j),$$

$$T3 = (1/R) * \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j)/(1+(i-j)^2),$$

$$T4 = -(1/R) * \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P(i,j) * LOG(P(i,j)/R+0.000001),$$

$$T5 = (1/R) * \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} ABS(i-j) * P(i,j),$$

where R is the number of picture element pairs, N the number of grey levels, and P(i,j) the spatial dependence matrix. If a picture is of dimension M by M then R is given by:

$R = 2*(M)*(M-1)$, for orientations 0° and 90°,

and

$R = 2*(M-1)*(M-1)$, for orientations 45° and 135°.

In the equation for T4 it is possible that the log of zero may occur for the ratio P(i,j)/R. This is circumvented, as shown, by the addition of a small delta. The equations for T3 and T4 are also known by the names inverse difference moment and entropy respectively [Haralick, et al., 1973].

The next type of table presented is the secondary

values table. This provides a summary of the 2nd-order values produced from the two constituent textures contained in the test picture. As an aid, a ratio relating the means of the background and foreground is calculated. This ratio MR is given by:

$$MR = ABS(BM-FM)/(BM+FM),$$

where BM is the background mean, FM is the foreground mean, and MR is assigned the value 0 if BM and FM are both 0. In the secondary values table PT is an abbreviation for point total and indicates the number of points used in calculating table values. The three letter abbreviations on the left margin of the table indicate which orientation and measure are used to produce the entries in that row of the table. The first two letters give the orientation and the third letter the measure, e.g., VTF is vertical F values measure, VTC is vertical C values measure, and LDF, HTF, RDF represent left diagonal, horizontal, and right diagonal F values measure respectively. At the bottom of each table are PTEX program parameters. These are the parameters which were specified to PTEX, the program used to generate 2nd-order pictures. _Vector length_ indicates how many points were looked at in generating a value. _Fluctuation threshold_ is the value r used to specify the range R for measure F as discussed in the previous chapter. Other thresholds include CHGTH and THS where CHGTH is a change threshold telling how

many points in a picture must be scanned before a change in the vector switching mechanism is allowed. THS is a two valued threshold, one value pertaining to the un-normalized F value produced and the other to the un-normalized C value produced. These two thresholds indicate how much the un-normalized values are allowed to change before the vector switching mechanism will function. The default for CHGTH is 2 and the default for THS is (2,2).

The last type of table is a boundary comparison table. It presents values comparing the final boundaries produced with ideal boundaries or the best that could be achieved. These ideal boundaries are produced by taking the binary mask pictures used to create the test pictures and applying the same 3 by 3 square gradient edge operator which is used to produce the final boundaries. The boundaries thus created represent the best possible that the process could hope to achieve.

Ideal boundaries are checked against final boundaries first, and then final boundaries checked against the ideal ones. This double comparison is done to take into account boundaries missing in one picture (final) which are present in the other (ideal). The larger the value produced by comparing the ideal to the final with respect to the value produced by comparing the final to the ideal, the more indicative it is that boundaries in the ideal are missing in the final. The converse situation, indicates that there are

superfluous boundaries in the final. The actual value produced by the comparison, is a measure of the separation between the boundaries. In comparing the final to the ideal, a boundary point in the final picture is found and using its spatial location, the distance to the nearest boundary point in the ideal picture is determined. This distance will be 0 if the boundary points correspond. If s(i) represents the set of separation distances for a comparison, then a final separation comparison value SC is determined as follows:

$$SC = \mathrm{SQRT}[(1/NEP) * \sum_{i=1}^{NEP} s(i)^2],$$

where NEP is the number of edge or boundary points in the picture which is being compared. Thus the value SC is the square root of the mean separation distance squared. The mean of the two SC values obtained is given in the table, as well as a ratio relating the number of edge points in the final picture to the ideal picture. NEPR, the ratio value, is given by:

$$NEPR = \mathrm{ABS}(INEP - FNEP)/INEP,$$

where INEP and FNEP are the number of edge points produced in the ideal and final pictures. On the whole, the smaller the values in the last column of the table, the better. In

all three types of tables, the abbreviation T.P. in the table title stands for Test Picture.

5.2 Artificial Test Results

Three artificial textured test pictures are used. The first of these is shown in Figure 5.1, and consists of two textures, one composed of vertical lines and the other of horizontal lines. Following this picture are two intermediate 2nd-order pictures. Figures 5.2 and 5.3 display the values F and C, as previously defined, using vertical and horizontal orientations respectively. The final extracted boundaries are shown in Figure 5.4. Test

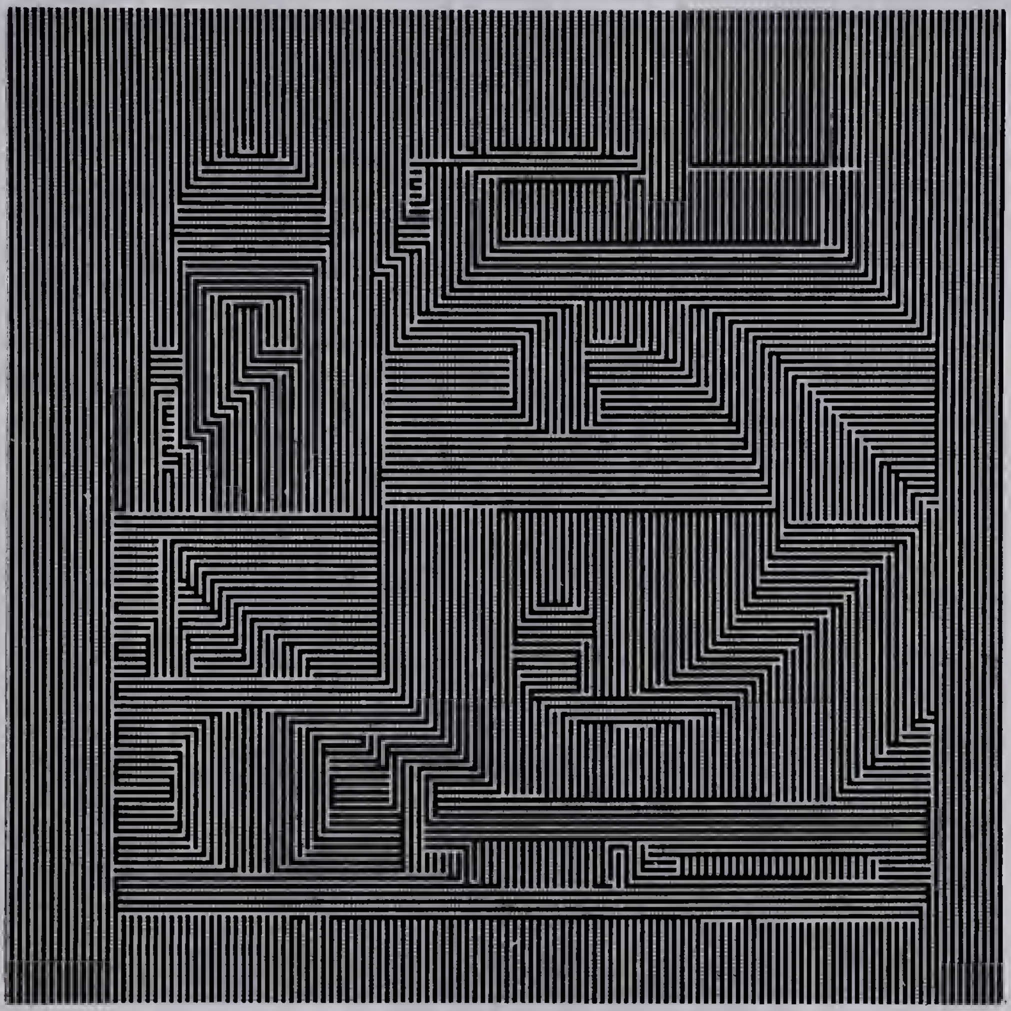

Figure 5.1 Test Picture #1

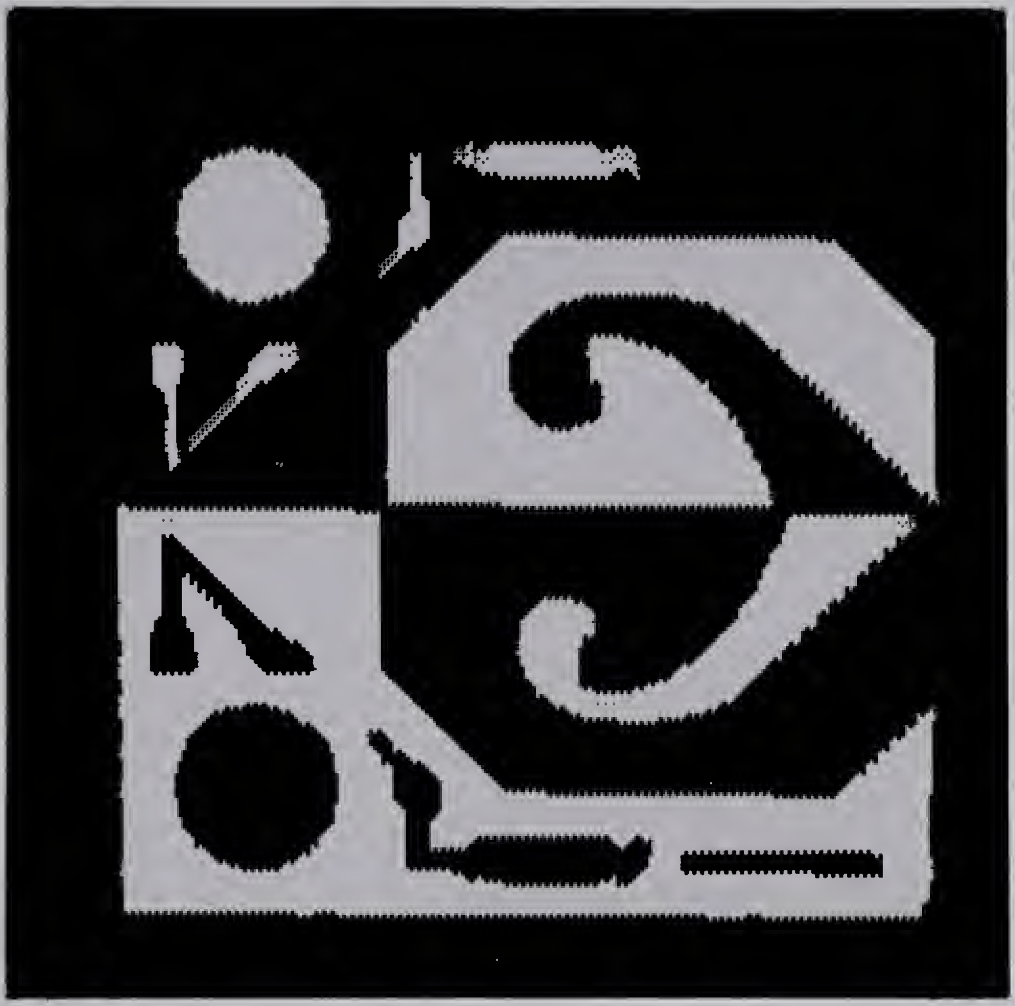

Figure 5.2 Test Picture #1 - Vertical F

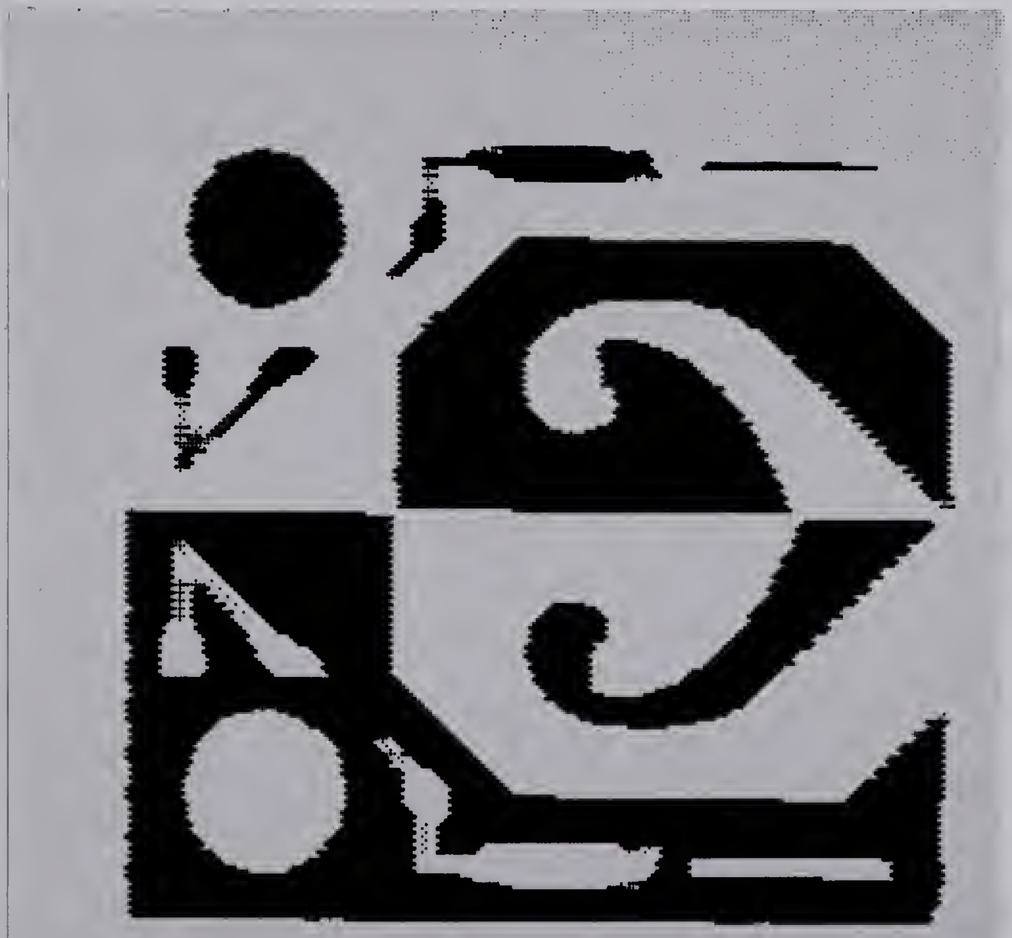

Figure 5.3 Test Picture #1 - Horizontal C

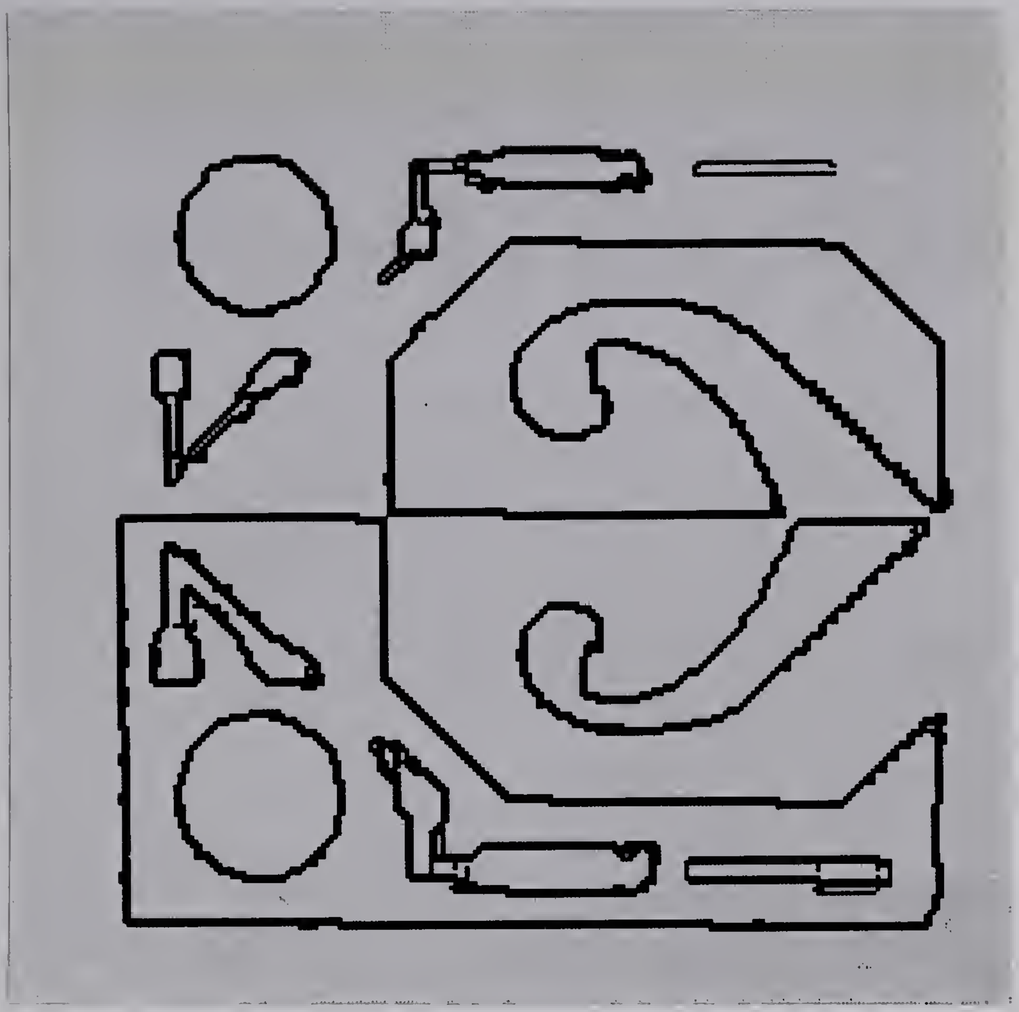

Figure 5.4 Test Picture #1 - Boundaries

picture #2 and the final borders for test picture #2 are shown in Figures 5.5 and 5.6, while test picture #3 and its final extracted borders are located in Figures 5.7 and 5.8. For test picture #2, the vertical background of test picture #1 is replaced with a checkerboard pattern that presents similar characteristics whether viewed horizontally or vertically. Test picture #3 is composed of two diagonal textures, one at 45° and the other at 135°. This picture is composed of coarser textures than those appearing in the previous test pictures.

Various information can be deduced from the pictorial results. Looking at the vertical F and horizontal C pictures of test picture #1, it can be seen that, given a

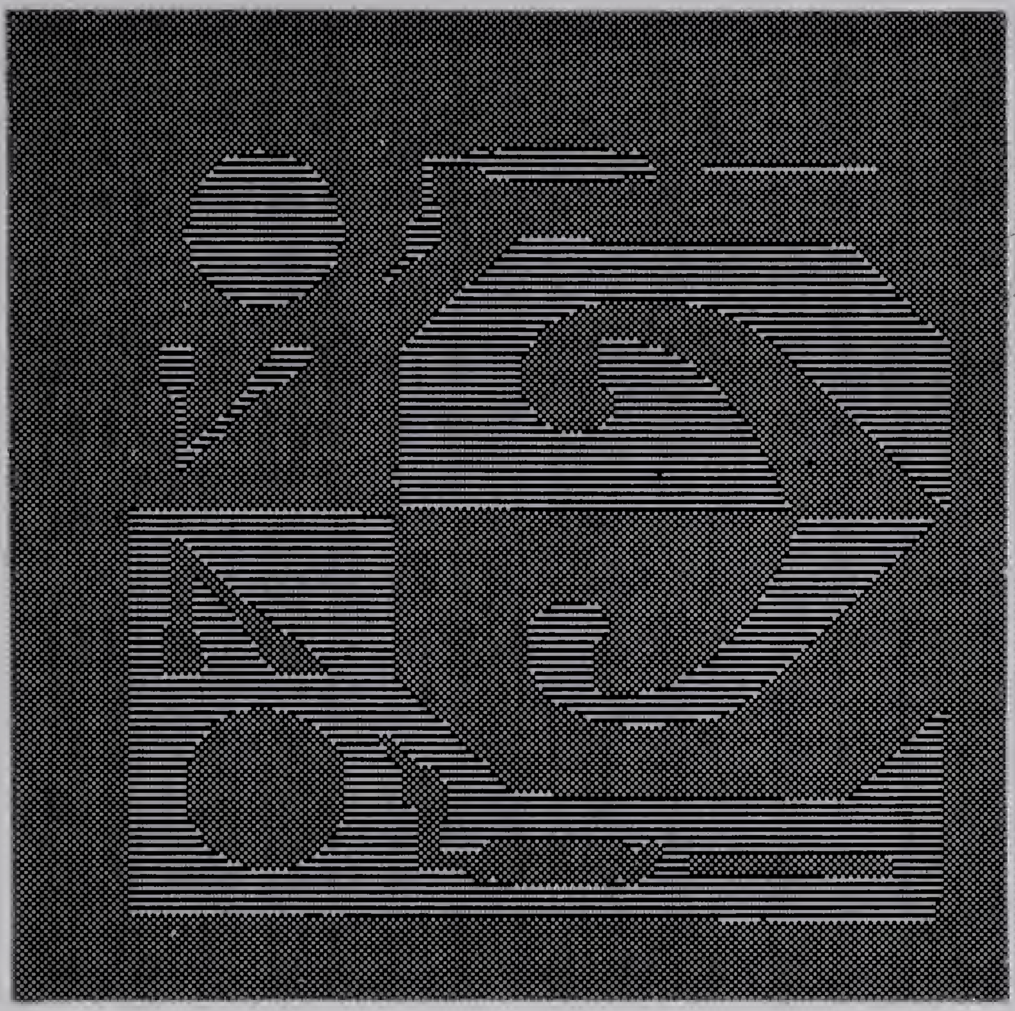

Figure 5.5 Test Picture #2

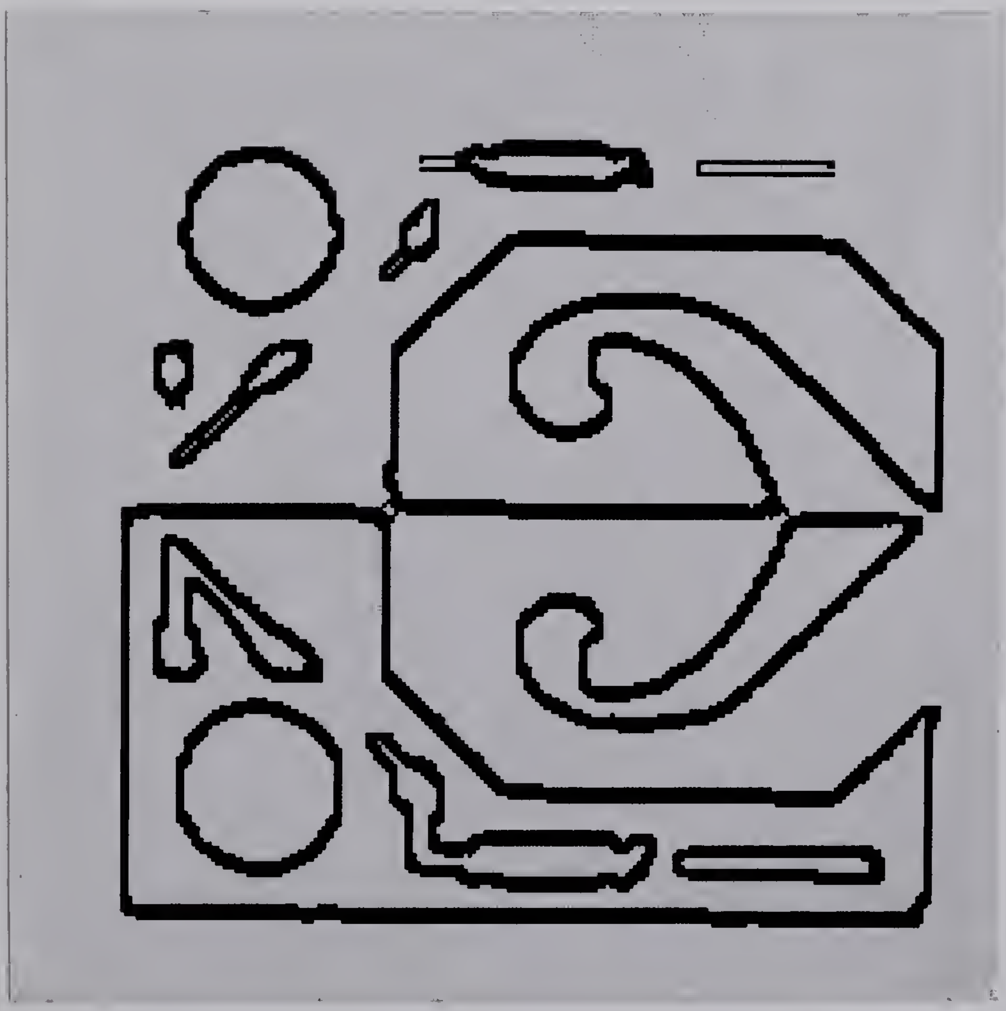

Figure 5.6 Test Picture #2 - Boundaries

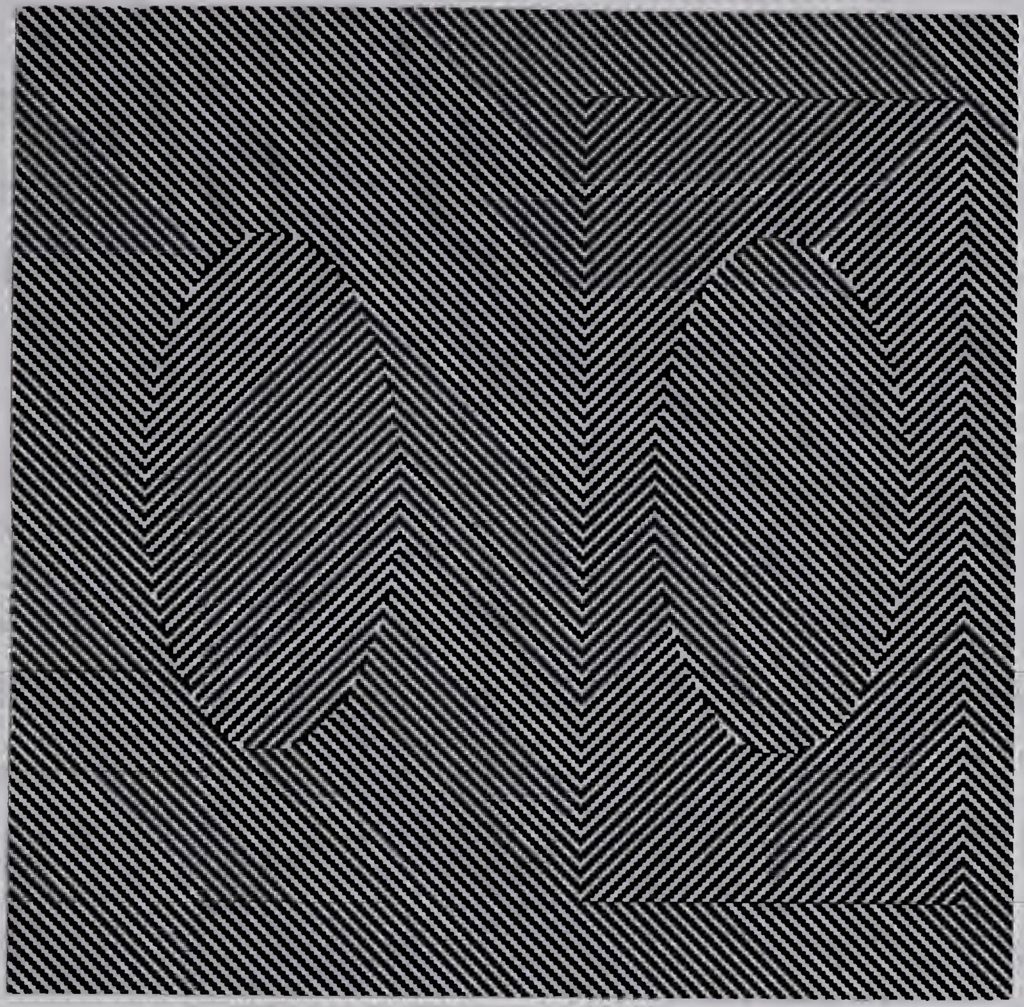

Figure 5.7 Test Picture #3

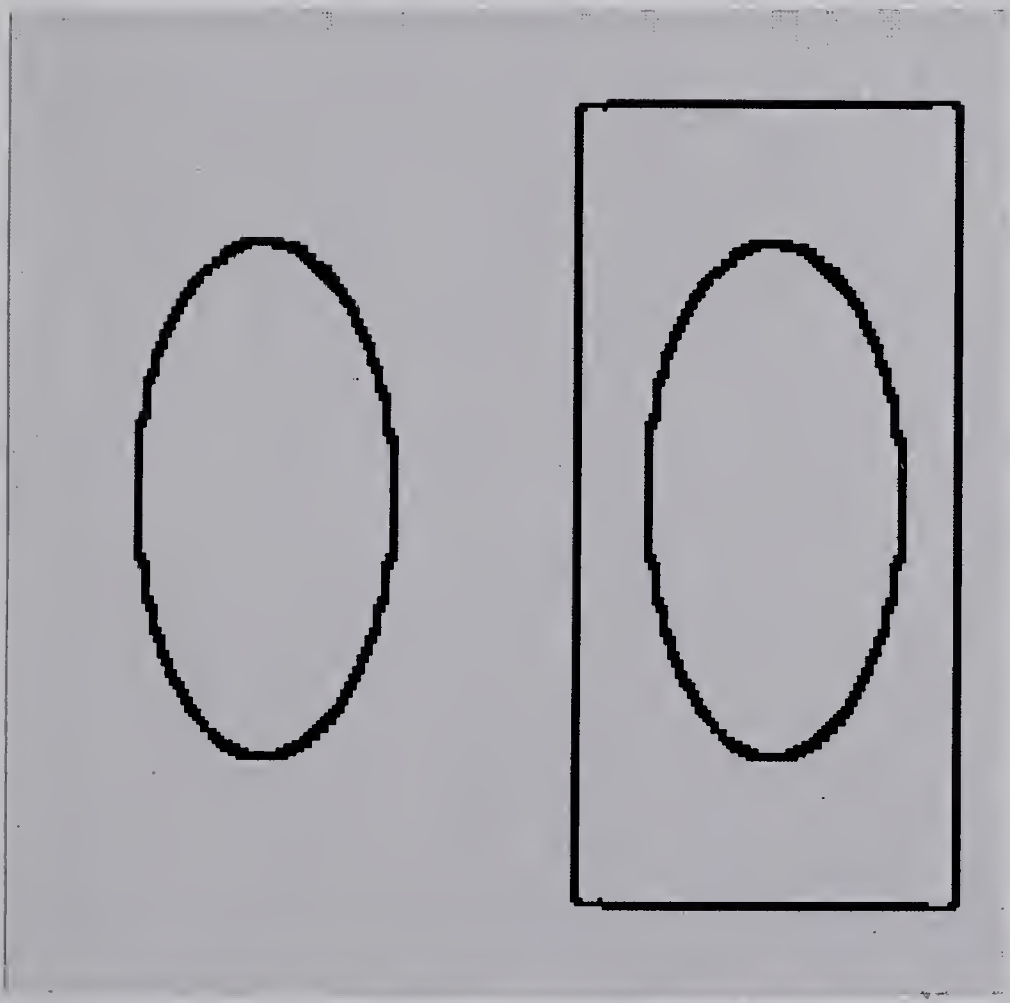

Figure 5.8 Test Picture #3 - Boundaries

regular texture and region sizes larger than the neighbourhood being analysed, good clear distinctions can be made between regions. Another point is that information not picked up in one scan orientation may be found in a different scan orientation. The small, very thin region at the top right of test picture #1 is barely noticable in the vertical picture and yet is strongly present in the horizontal one. Thus various information contained in 2nd-order pictures can be combined to produce a final picture. The boundary picture for test picture #2 exhibits characteristics similar to those found in the first test set. Those portions of the picture where boundaries are missing or unclear correspond to areas in the original test picture where textured regions are very small and/or very close together. In contrast, the boundaries of test picture #3, where textured regions are of a larger size relative to the neighbourhood being measured, has clear and distinct boundaries.

The tabular data relating to the test pictures also provides useful information. Tables I, II, and III contain information pertaining to the characteristics of the test pictures. It can be seen that the textures in all three test sets possess the same average brightness and standard deviations. Therefore calculating these values will be of no help and to distinguish regions it is necessary to determine textural properties. Looking at the spatial dependence matrix measures for test picture #1, it is

Table I

Texture Characteristics of T.P. #1

T.P. #1	Background	Foreground
Name	vertical lines	horizontal lines
Mean	31.5	31.5
S.D.	31.5	31.5
0 degrees		
T1	0.0	1984.5
T2	3969.0	0.0
T3	0.00025	1.0
T4	0.30103	0.30103
T5	63.0	0.0
45 degrees		
T1	0.0	0.0
T2	3969.0	3969.0
T3	0.00025	0.00025
T4	0.30103	0.30103
T5	63.0	63.0
90 degrees		
T1	1984.5	0.0
T2	0.0	3969.0
T3	1.0	0.00025
T4	0.30103	0.30103
T5	0.0	63.0
135 degrees		
T1	0.0	0.0
T2	3969.0	3969.0
T3	0.00025	0.00025
T4	0.30103	0.30103
T5	63.0	63.0

Background and foreground are two fine lined textures differing in orientation by 90 degrees. White portions have grey value 63 and dark portions 0.

Table II

Texture Characteristics of T.P. #2

T.P. #2	Background	Foreground
Name	checkerboard	horizontal lines
Mean	31.5	31.5
S.D.	31.5	31.5
0 degrees		
T1	0.0	1984.5
T2	3969.0	0.0
T3	0.00025	1.0
T4	0.30103	0.30103
T5	63.0	0.0
45 degrees		
T1	1984.5	0.0
T2	0.0	3969.0
T3	1.0	0.00025
T4	0.30103	0.30103
T5	0.0	63.0
90 degrees		
T1	0.0	0.0
T2	3969.0	3969.0
T3	0.00025	0.00025
T4	0.30103	0.30103
T5	63.0	63.0
135 degrees		
T1	1984.5	0.0
T2	0.0	3969.0
T3	1.0	0.00025
T4	0.30103	0.30103
T5	0.0	63.0

Background and foreground textures both consist of fine patterns.

Table III

Texture Characteristics of T.P. #3

T.P. #3	Background	Foreground
Name	diagonal lines 135 degrees	diagonal lines 45 degrees
Mean	31.5	31.5
S.D.	31.5	31.5
0 degrees		
T1	992.25	992.25
T2	1984.5	1984.5
T3	0.50013	0.50013
T4	0.60206	0.60206
T5	31.5	31.5
45 degrees		
T1	0.0	1984.5
T2	3969.0	0.0
T3	0.00025	1.0
T4	0.30103	0.30103
T5	63.0	0.0
90 degrees		
T1	992.25	992.25
T2	1984.5	1984.5
T3	0.50013	0.50013
T4	0.60206	0.60206
T5	31.5	31.5
135 degrees		
T1	1984.5	0.0
T2	0.0	3969.0
T3	1.0	0.00025
T4	0.30103	0.30103
T5	0.0	63.0

The textures in this picture are coarser than those in the first two test pictures.

evident that there is only a distinguishable difference in the textures when using scan orientations of 0° and 90°. This corresponds to results in Table IV, the secondary values table for test picture #1. A similar correspondence of results and orientation is evident for test pictures #2 and #3 in Tables V and VI respectively. Information in Tables VII, VIII, and IX, the boundary comparison tables, confirms what is visualy apparent in the pictures presented. The SC mean value is low in all cases (less than 1.5), indicating a fairly good fit for the final boundaries. Moreover, test picture #3 which appears to have the best final boundaries has the lowest SC mean value (0.6411) and test picture #2, which presents the poorest looking final boundaries, has the highest SC mean value (1.4445). Thus,

Table IV

Secondary Values for T.P. #1

T.P. #1	Background PT = 28832		Foreground PT = 8019		MR
	Mean	S.D.	Mean	S.D.	
VTF	0.00	0.00	63.00	0.00	1.00
VTC	0.00	0.00	63.00	0.00	1.00
LDF	63.00	0.00	63.00	0.00	0.00
LDC	63.00	0.00	63.00	0.00	0.00
HTF	63.00	0.00	0.00	0.00	1.00
HTC	63.00	0.00	0.00	0.00	1.00
RDF	63.00	0.00	63.00	0.00	0.00
RDC	63.00	0.00	63.00	0.00	0.00

PTEX Program Parameters:
vector length = 5
fluctuation threshold = 0
other thresholds = default

Table V

Secondary Values for T.P. #2

T.P. #2	Background PT = 28832		Foreground PT = 8019		MR
	Mean	S.D.	Mean	S.D.	
VTF	63.00	0.00	63.00	0.00	0.00
VTC	63.00	0.00	63.00	0.00	0.00
LDF	0.00	0.00	63.00	0.00	1.00
LDC	0.00	0.00	63.00	0.00	1.00
HTF	63.00	0.00	0.00	0.00	1.00
HTC	63.00	0.00	0.00	0.00	1.00
RDF	0.00	0.00	63.00	0.00	1.00
RDC	0.00	0.00	63.00	0.00	1.00

PTEX Prcgram Parameters:
vector length = 5
fluctuation threshold = 0
other thresholds = default

Table VI

Secondary Values for T.P. #3

T.P. #3	Background PT = 22840		Foreground PT = 8015		MR
	Mean	S.D.	Mean	S.D.	
VTF	31.00	0.00	31.00	0.00	0.00
VTC	32.00	0.00	32.00	0.00	0.00
LDF	0.00	0.00	63.00	0.00	1.00
LDC	0.00	0.00	63.00	0.00	1.00
HTF	31.00	0.00	31.00	0.00	0.00
HTC	32.00	0.00	32.00	0.00	0.00
RDF	63.00	0.00	0.00	0.00	1.00
RDC	63.00	0.00	0.00	0.00	1.00

PTEX Prcgram Parameters:
vector length = 9
fluctuation threshold = 0
other thresholds = default

Table VII

Boundary Comparison for T.P. #1

T.P. #1	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	1.8879	0.3839	1.1359
NEP	6359	6376	0.0027

Table VIII

Boundary Comparison for T.P. #2

T.P. #2	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	2.4452	0.4439	1.4445
NEP	6359	6077	0.0443

Table IX

Boundary Comparison for T.P. #3

T.P. #3	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	0.8557	0.4265	0.6411
NEP	2788	2320	0.1679

the SC mean value produced agrees with subjective visual judgements made by humans. The ratio of number of edge points in the final to ideal boundaries (NEPR) is a poor indicator of boundary fit. This is due to the ratio being too sensitive to the value of the denominator, which can vary widely from test set to test set, and on minor fluctuations in edge thickness between the final and ideal boundaries.

5.3 Natural Test Results

Five test sets composed of natural textures are used, of which the first two are basically the same. The first, test picture #4 in Figure 5.9, consists of a horizontal fine woodgrain texture embedded in a coarse vertical woodgrain texture. The region shape of the embedded texture is a square in this case. Subsequent to this are Figures 5.10 and 5.11, which are the vertical F measure and horizontal C measure respectively, and Figures 5.12 and 5.13, which are the final boundaries and final boundaries overlaid on the original texture test picture. In processing test picture #4, the fluctuation threshold was set to 2, i.e., differences less than and equal to 2 are treated as 0. It was also considered that if some preprocessing of the textured picture were performed then perhaps the use of a fluctuation threshold would not be necessary. This preprocessing would involve a minor filtering operation to eliminate, at least to some degree, minute fluctuations.

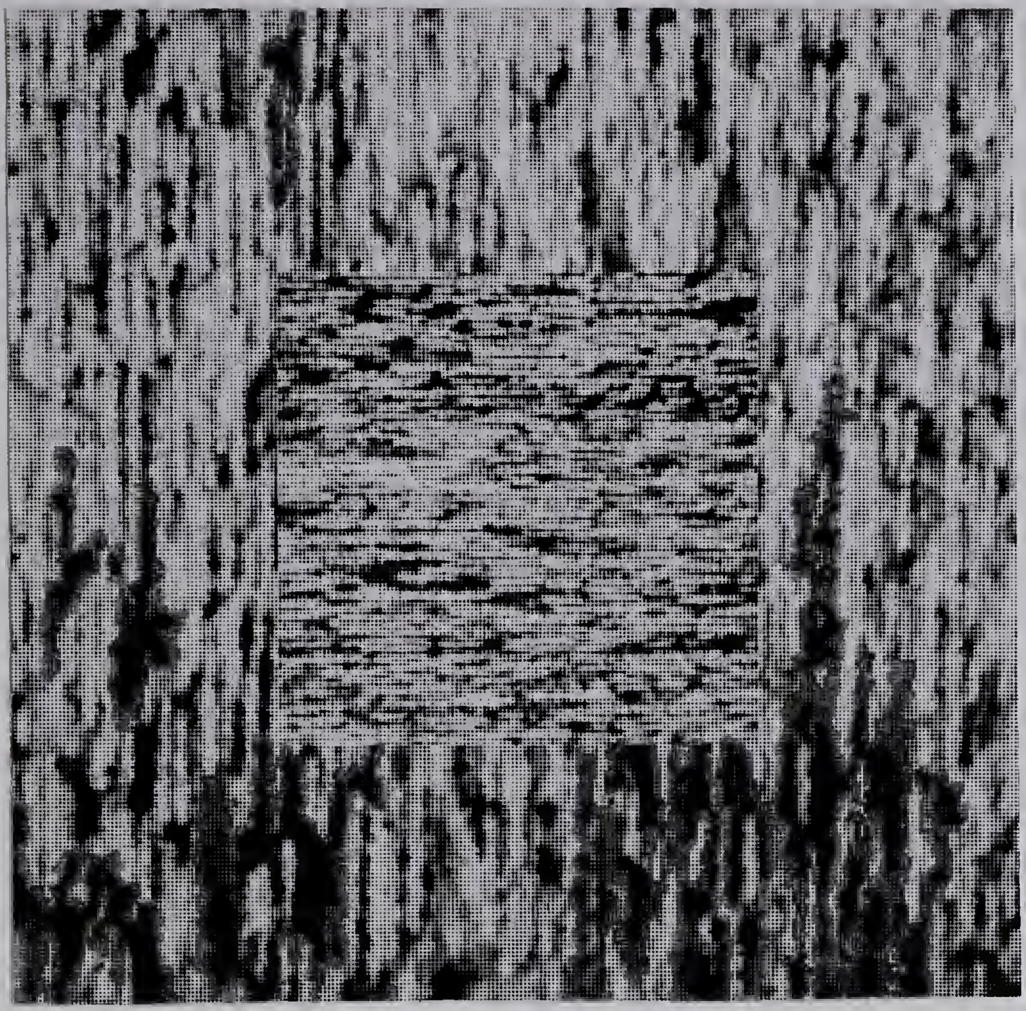

Figure 5.9 Test Picture #4

One way to accomplish this is to perform an averaging operation. A two by two averaging of the picture could eliminate undesired fluctuations and yet leave the desired information intact. Any slight reduction in contrast produced by averaging can be compensated for by doing a minor amount of grey level enhancement on the picture, e.g., by mapping a smaller grey level range into a larger one. Specifically, mapping the grey level range 2-61 into range 0-63 will cause a slight spreading apart of the grey level values with a resultant slight increase in contrast. It was found that slightly better results are obtained if enhancement is followed by averaging than if the reverse procedure is followed. Test picture #4 was processed in this manner to produce test picture #5. Figures 5.14, 5.15,

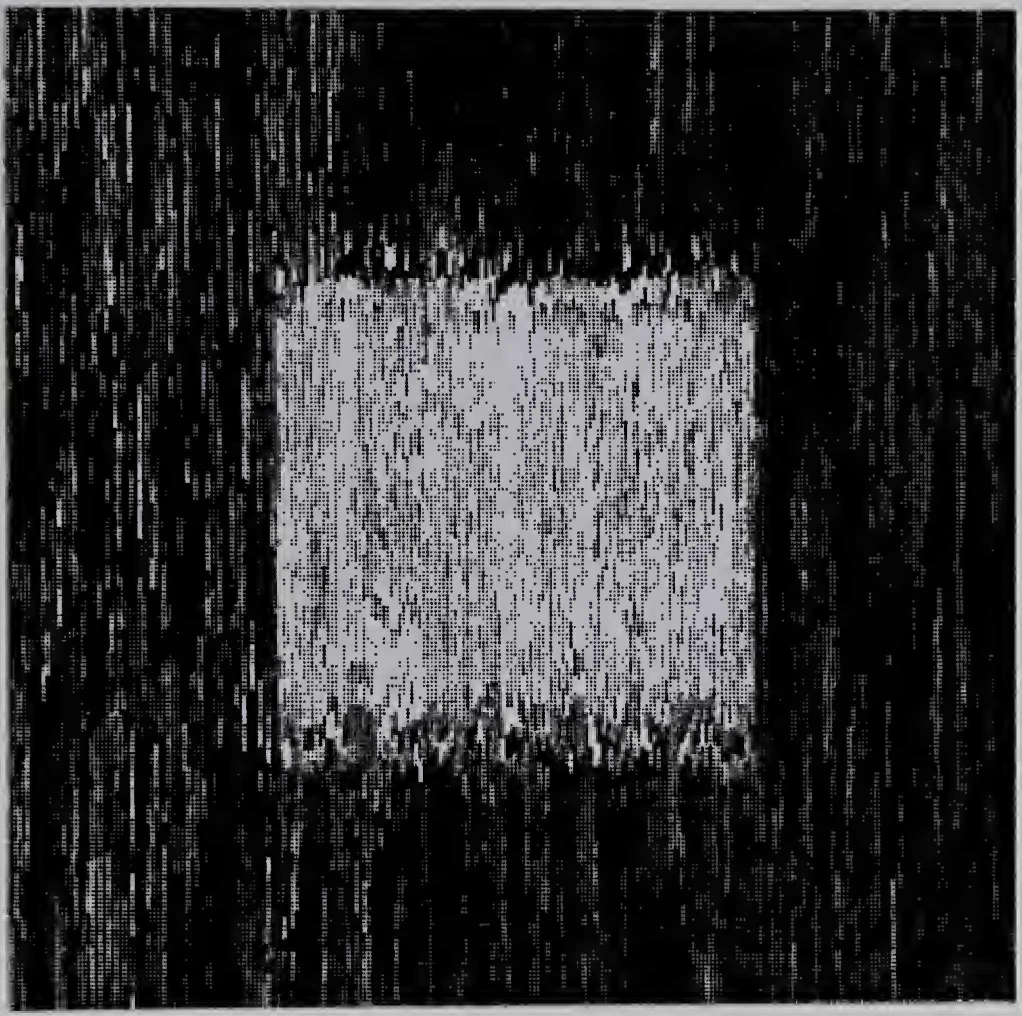

Figure 5.10 Test Picture #4 - Vertical F

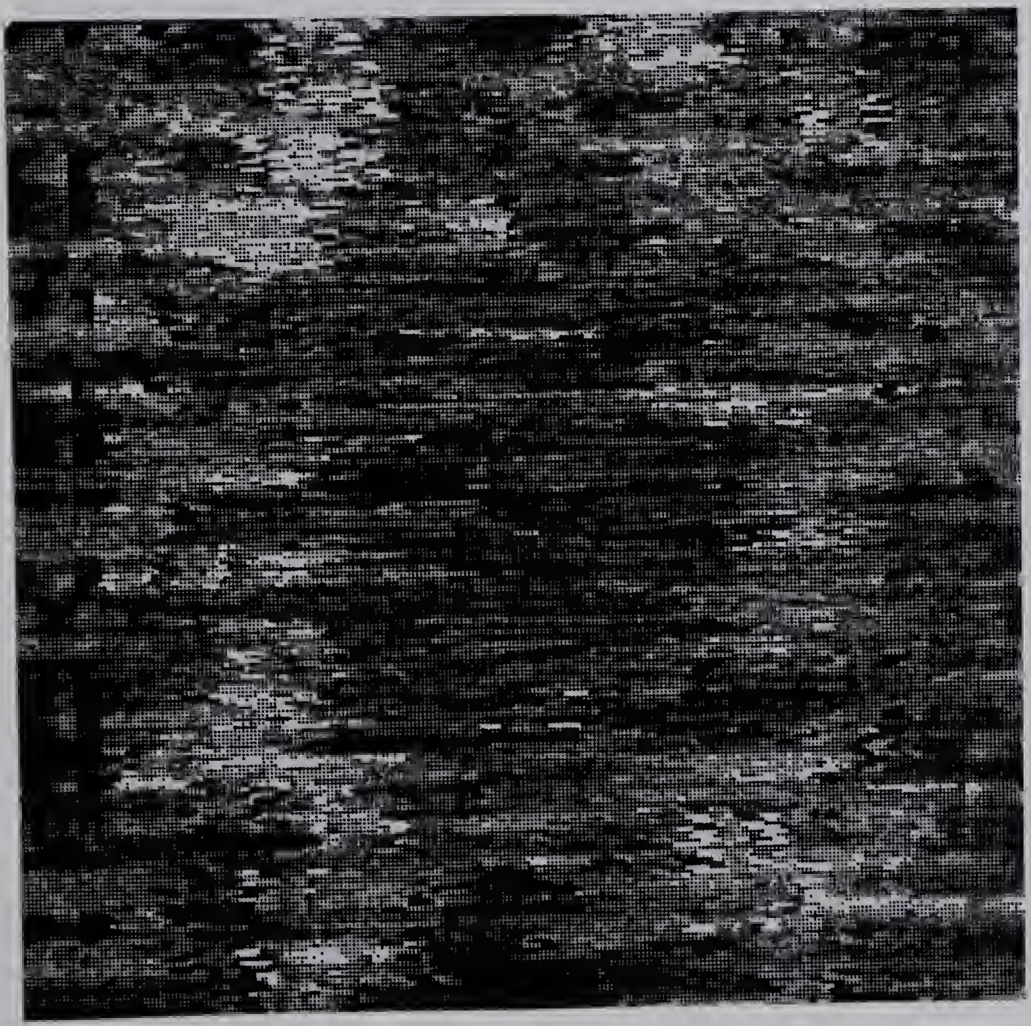

Figure 5.11 Test Picture #4 - Horizontal C

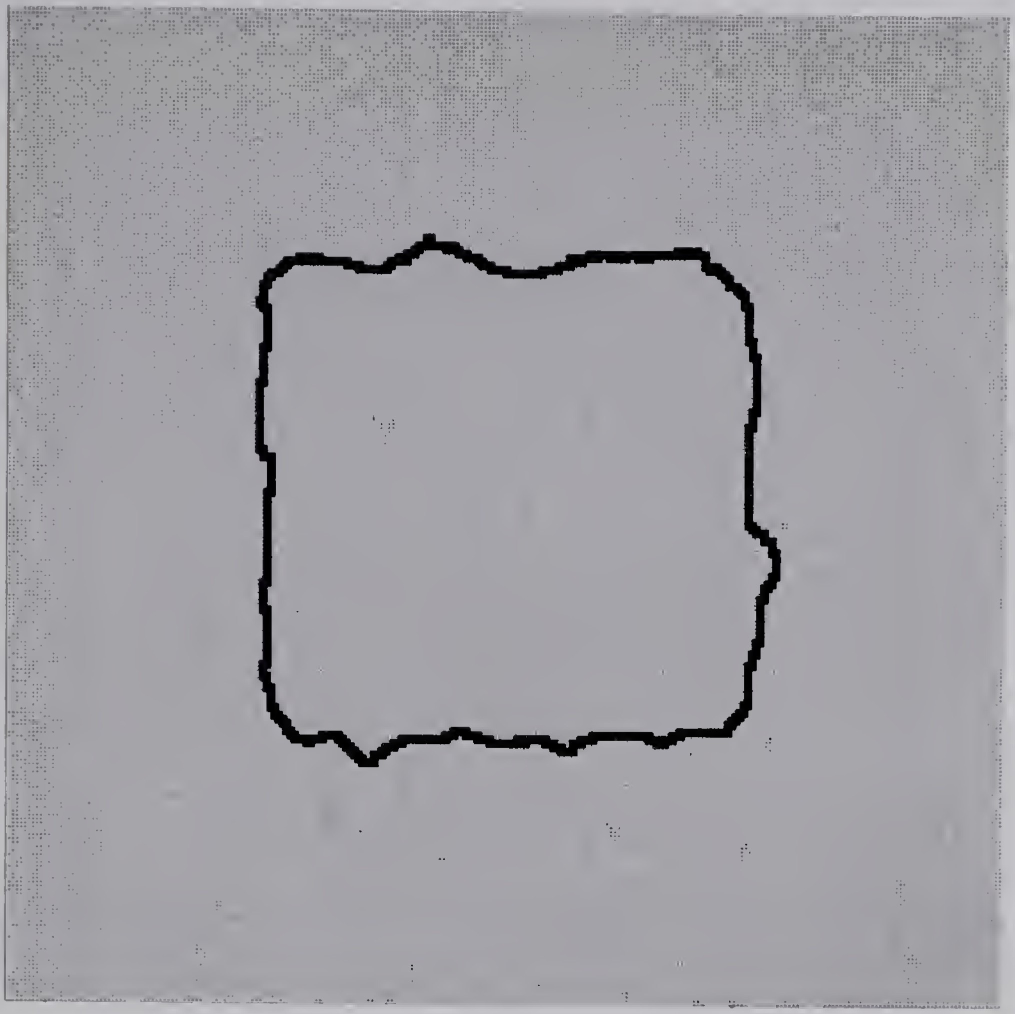

Figure 5.12 Test Picture #4 - Boundaries

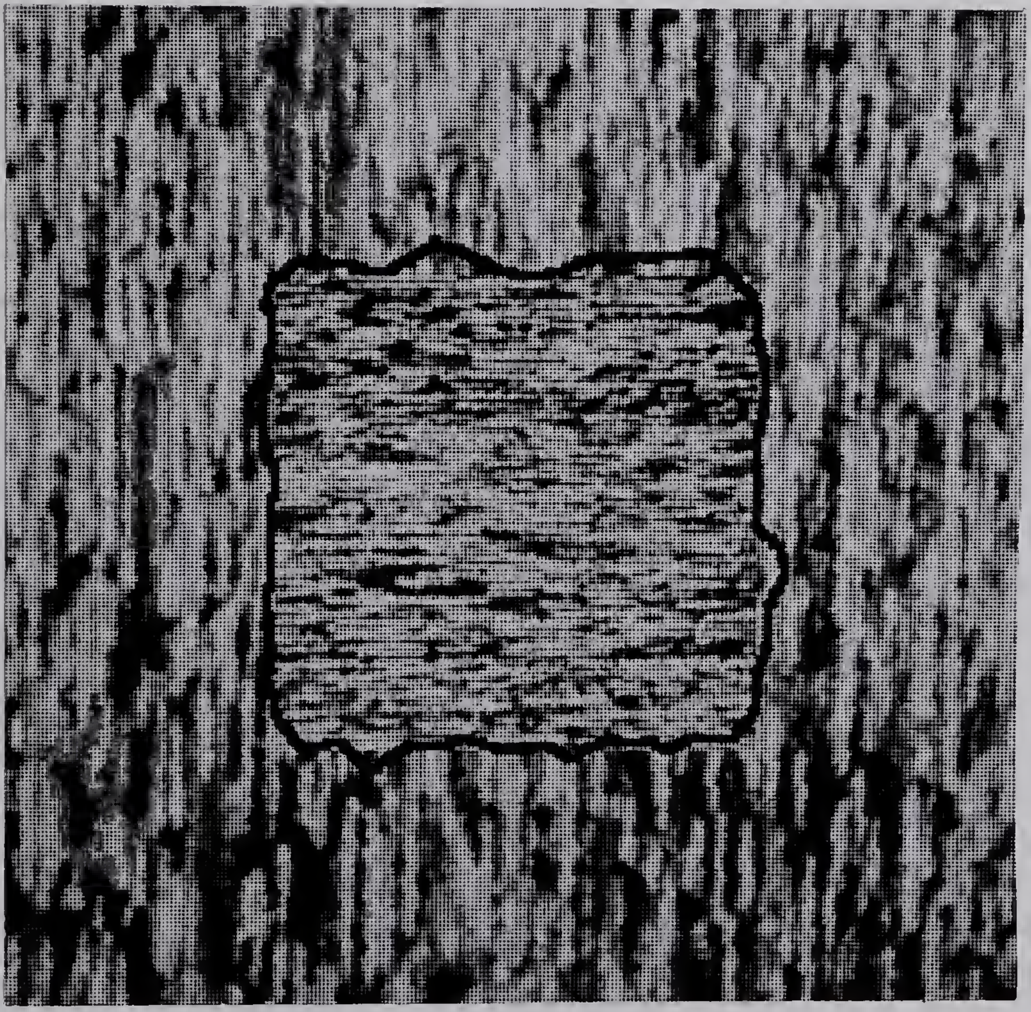

Figure 5.13 Test Picture #4 - Boundaries Overlaid

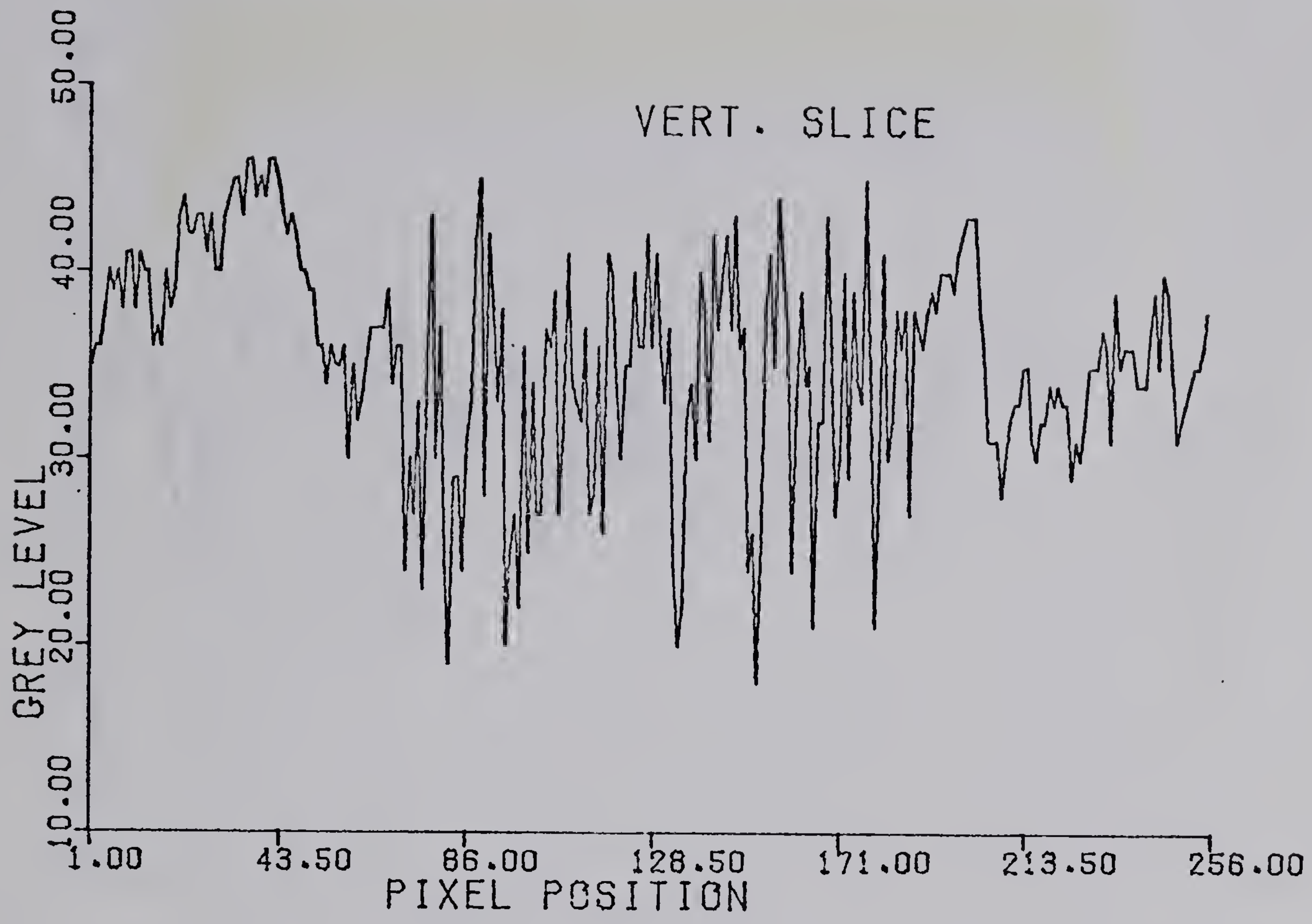

Figure 5.14 Test Picture #4 - Vertical Slice

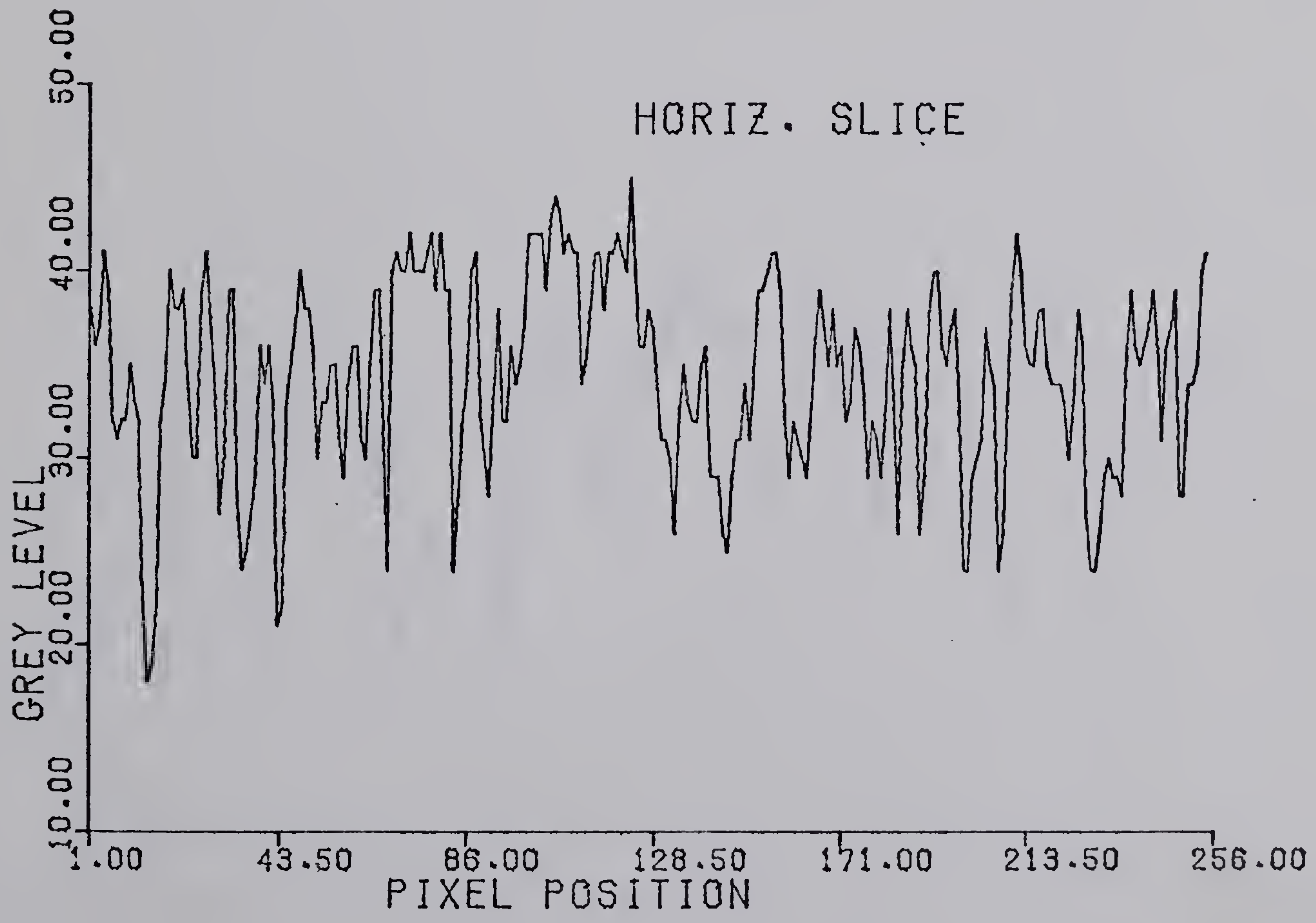

Figure 5.15 Test Picture #4 - Horizontal Slice

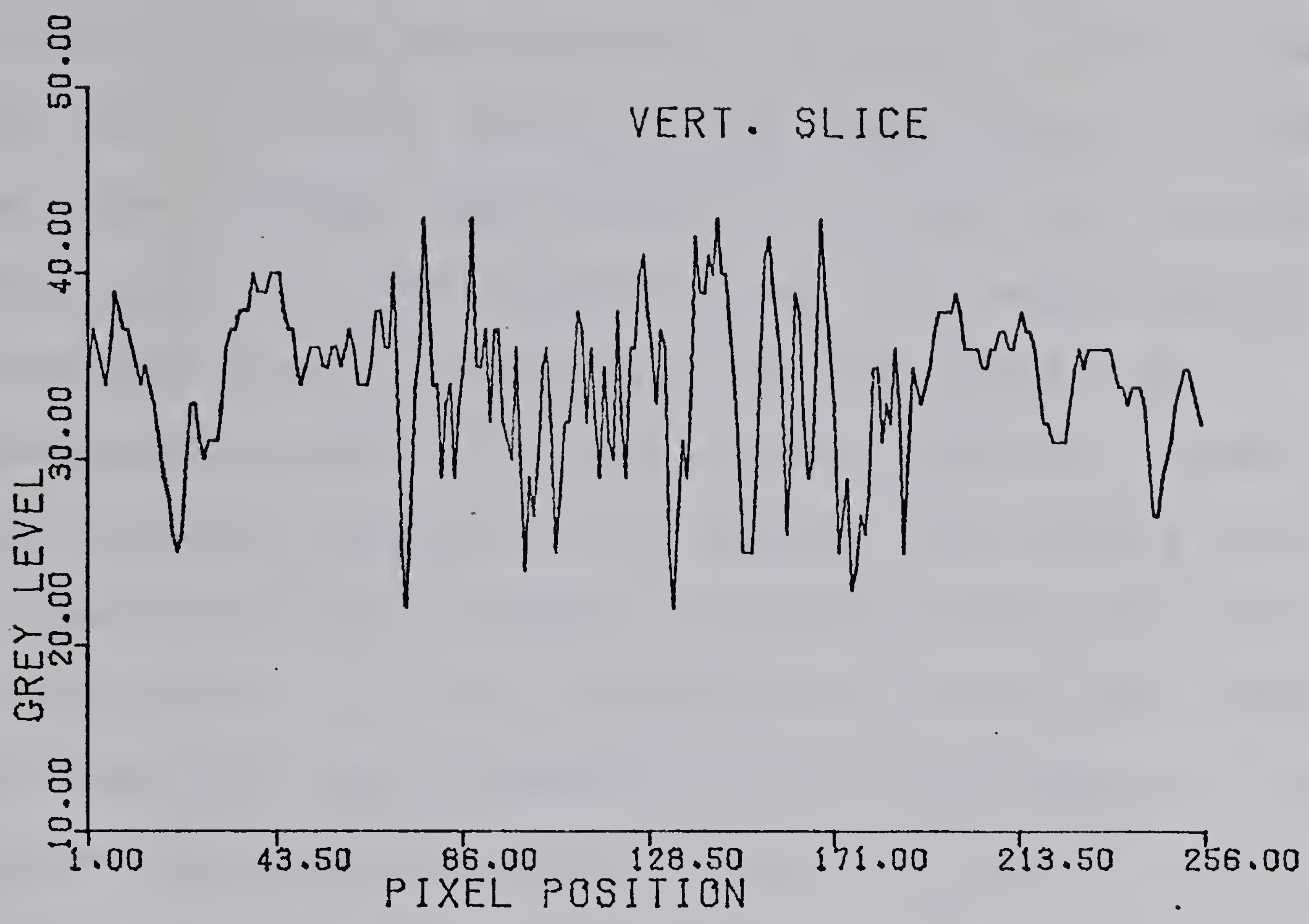

Figure 5.16 Test Picture #5 - Vertical Slice

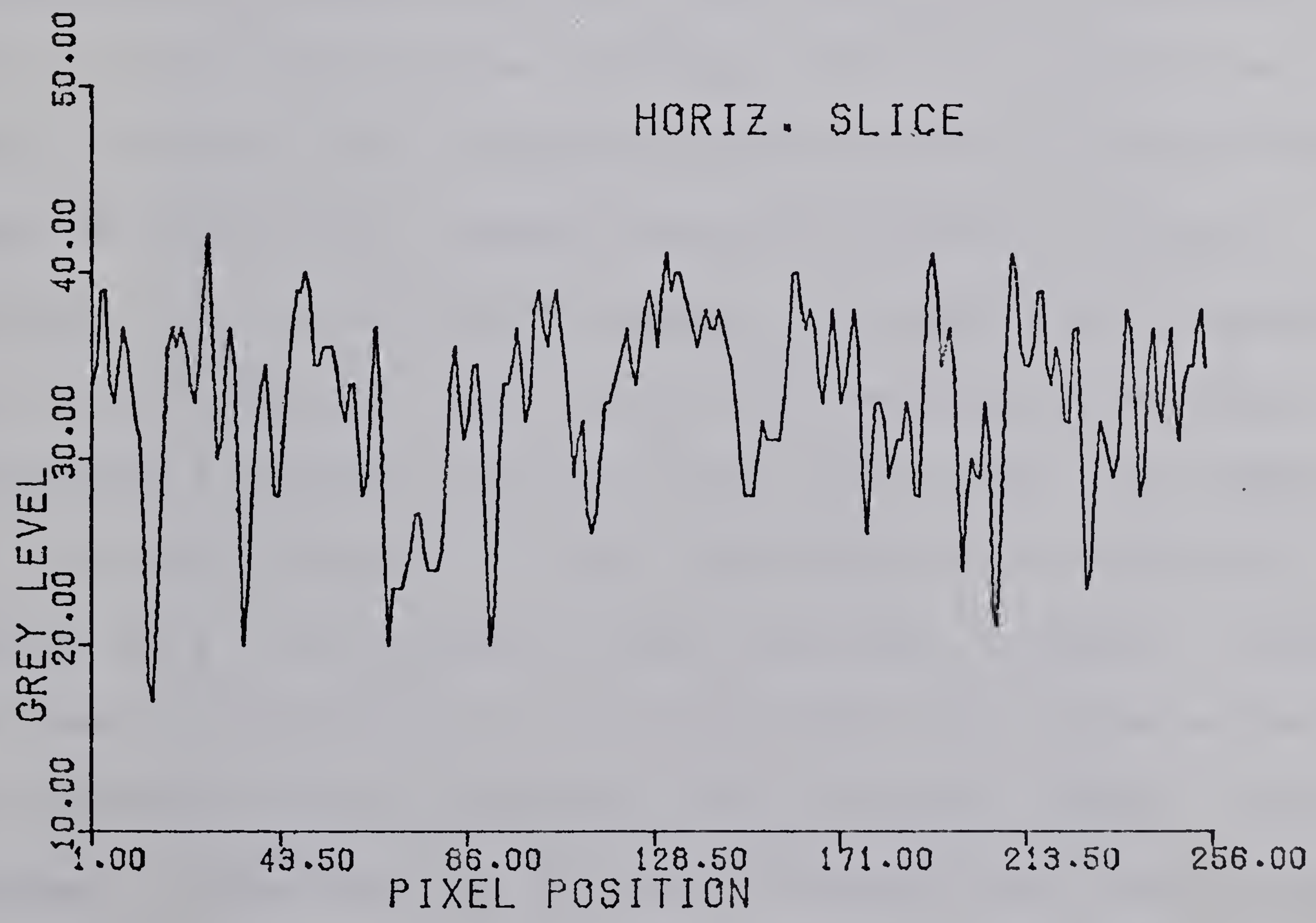

Figure 5.17 Test Picture #5 - Horizontal Slice

and 5.16, 5.17 show the effects of the preprocessing. The first pair of figures plots the grey level values of a slice taken midway through test picture #4 in first the vertical direction and then the horizontal one. The second pair of figures show similar information for test picture #5. Inspecting the pairs of figures, which illustrate linear slices through a picture, it is evident that coarser parts of a texture are less affected by preprocessing than finer textured parts, e.g., the midportion of the vertical slice indicating much more distortion than the end portions. The contrast after preprocessing is also less than in the original, even though a slight amount of enhancement is performed. Presented in Figures 5.18 and 5.19 are the pictures representing the vertical F measure and horizontal C measure of test picture #5. The fluctuation threshold was set to 0 to produce these results. The final boundaries are shown in Figure 5.20. Succeeding this is test picture #6, given in Figure 5.21, which contains adjacent irregular textures, one finer than the other. Following are Figures 5 .22, 5.23, and 5.24, that contain the vertical C measure, horizontal F measure, and the final boundaries. In Figure 5 .25, is test picture #7. This consists of the woodgrain texture from test picture #4 and the finer irregular texture from test picture #6. It is a difficult test picture due to the coarseness of the textures and the small regions close together. Shown are the vertical C measure and horizontal F measure pictures in Figures 5.26 and 5.27, and the final

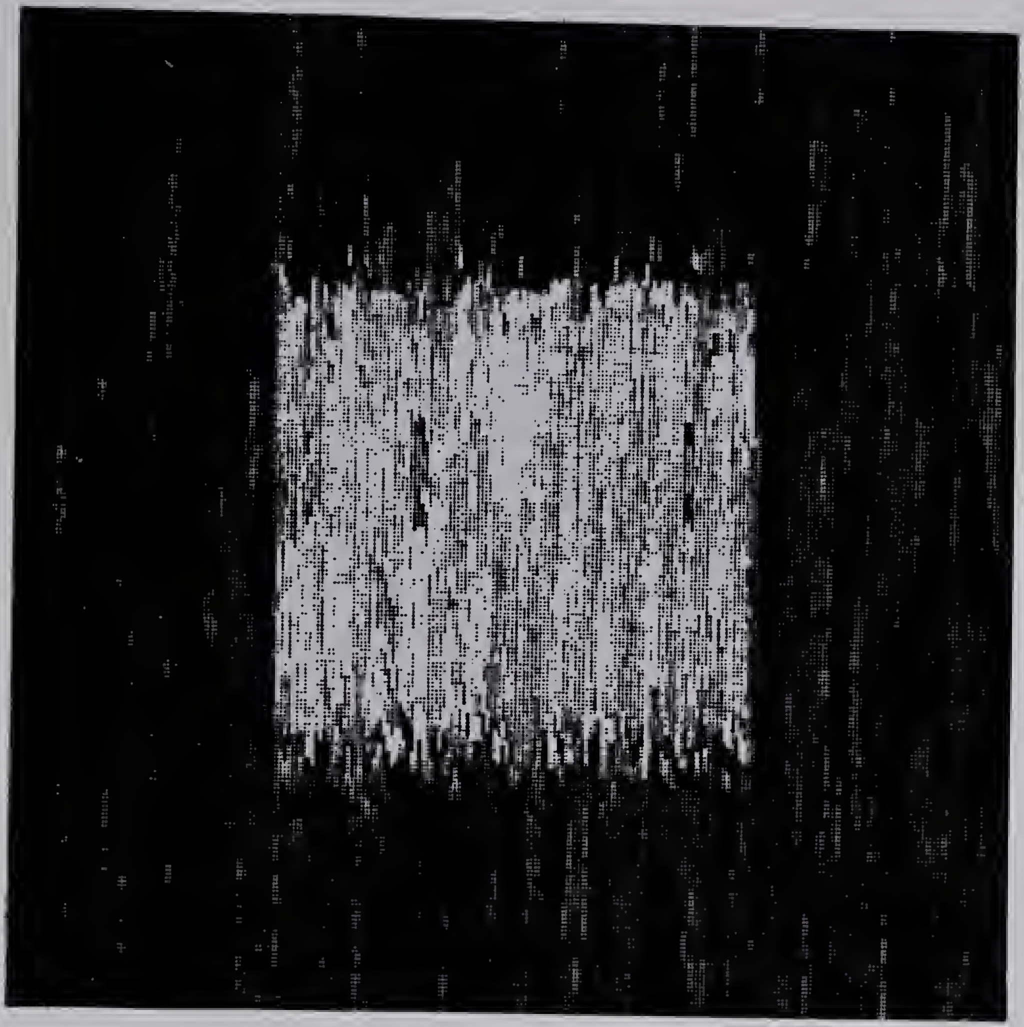

Figure 5.18 Test Picture #5 - Vertical F

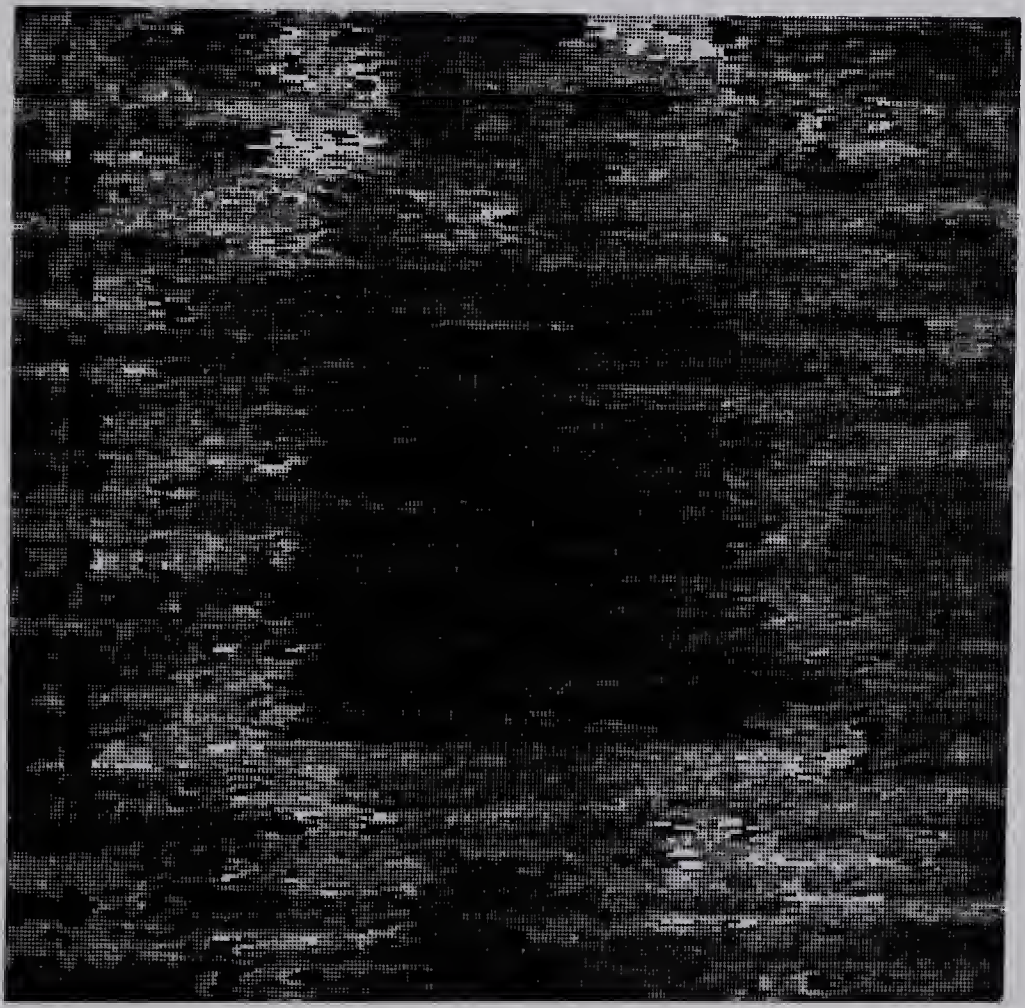

Figure 5.19 Test Picture #5 - Horizontal C

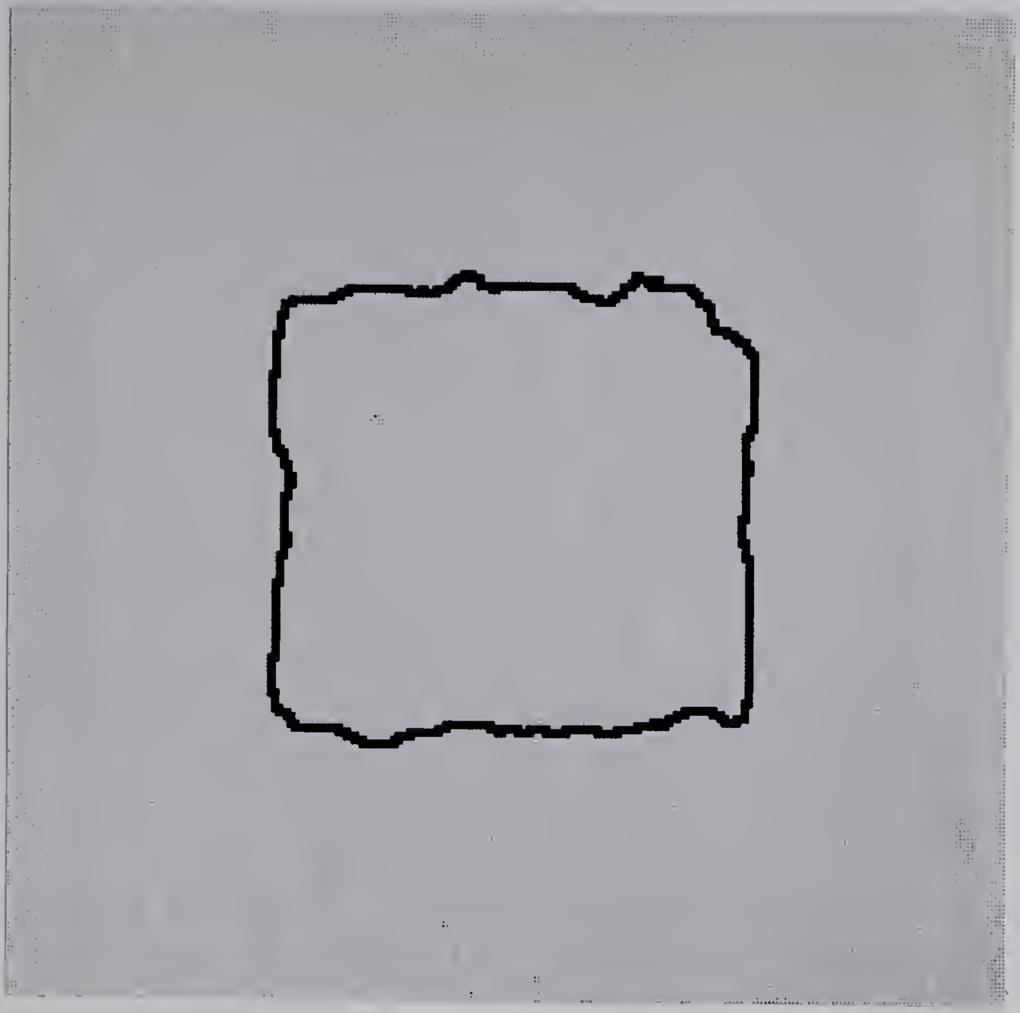

Figure 5.20 Test Picture #5 - Boundaries

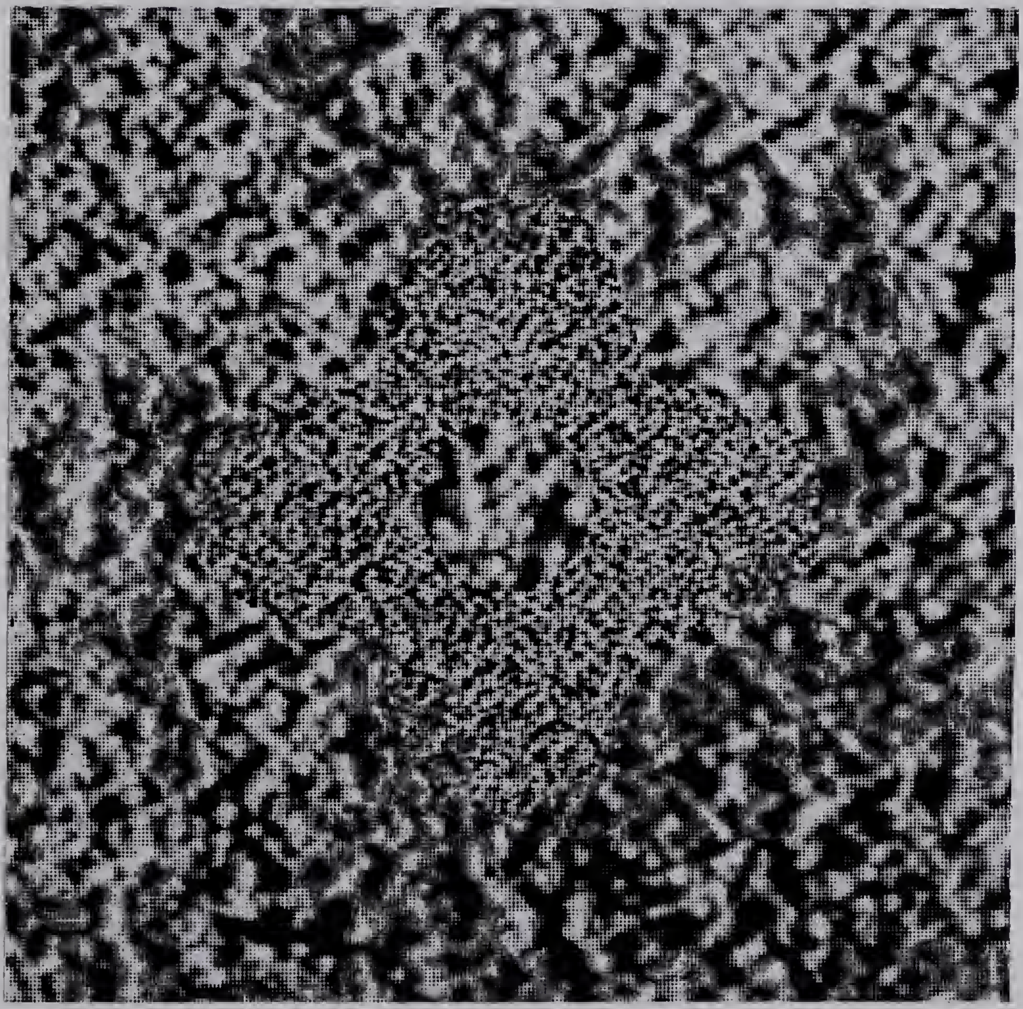

Figure 5.21 Test Picture #6

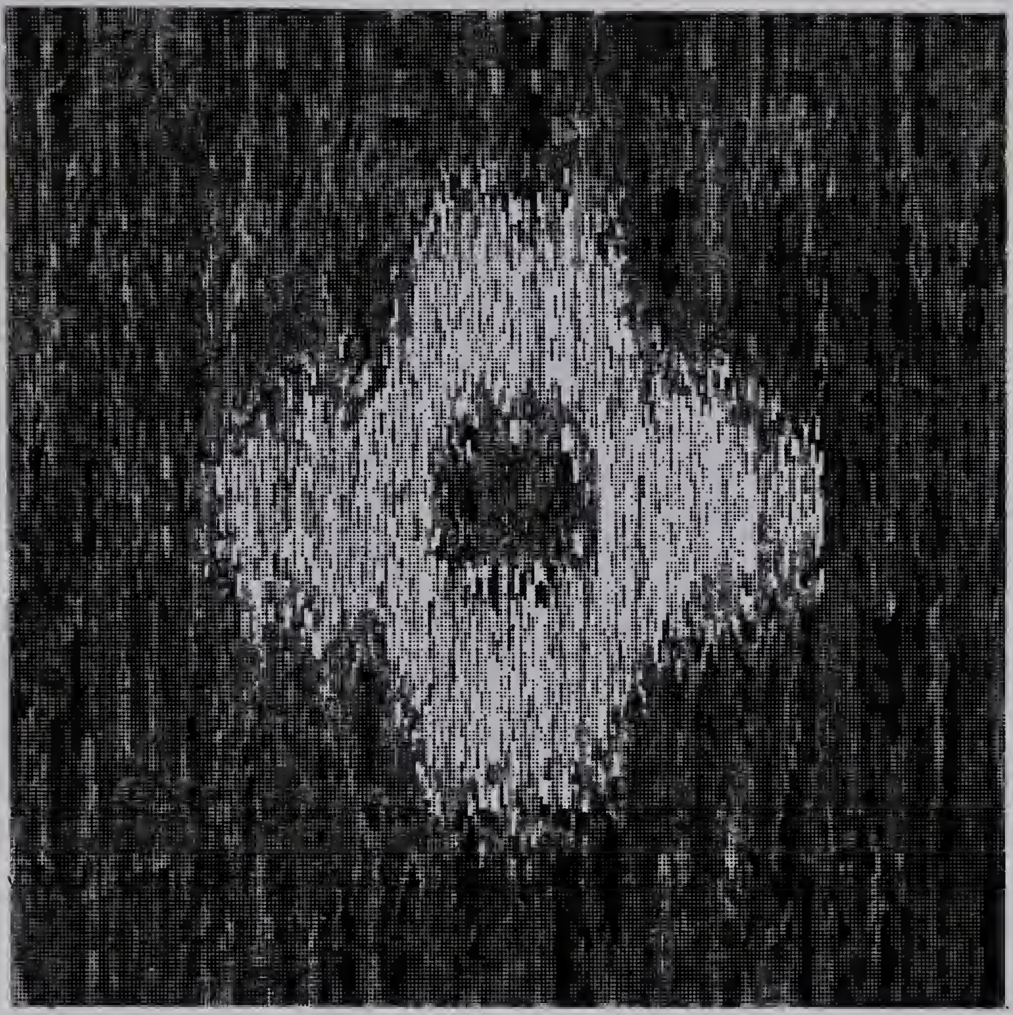

Figure 5.22 Test Picture #6 - Vertical C

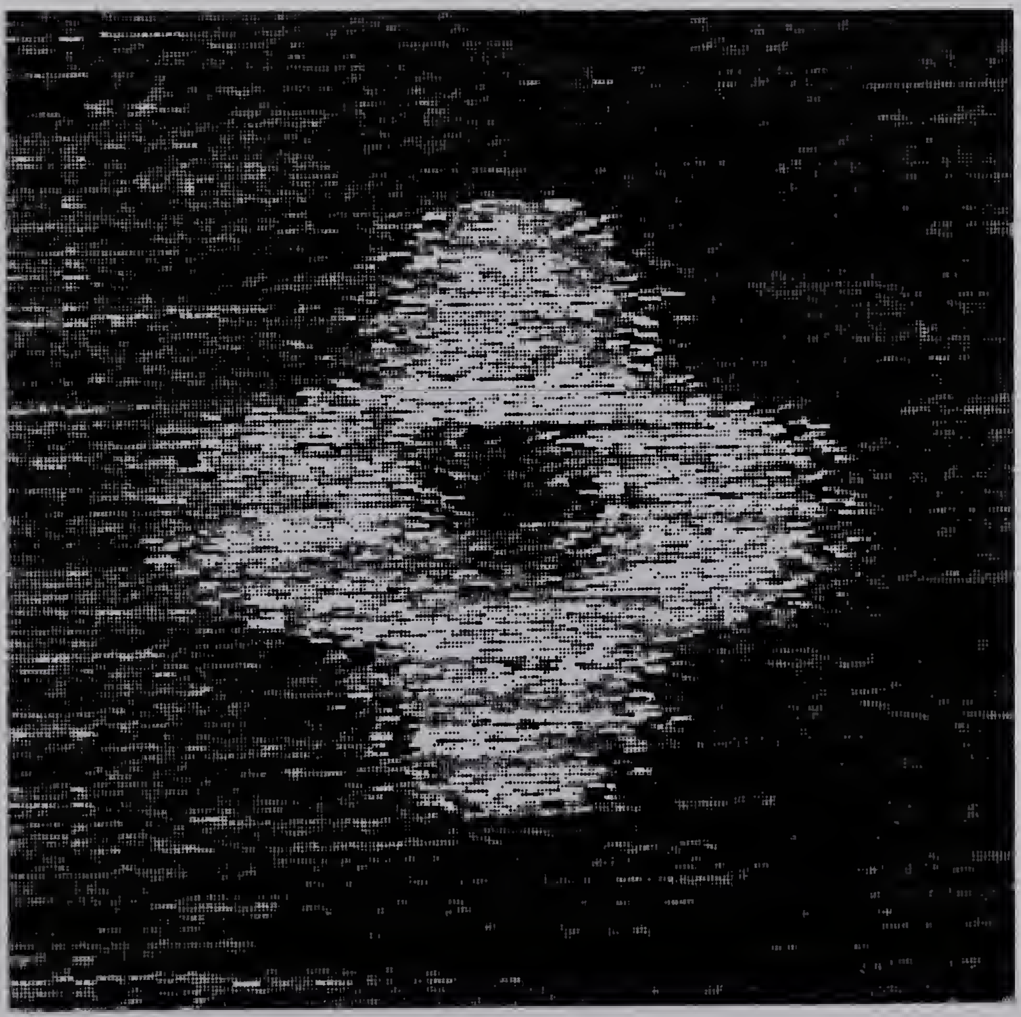

Figure 5.23 Test Picture #6 - Horizontal F

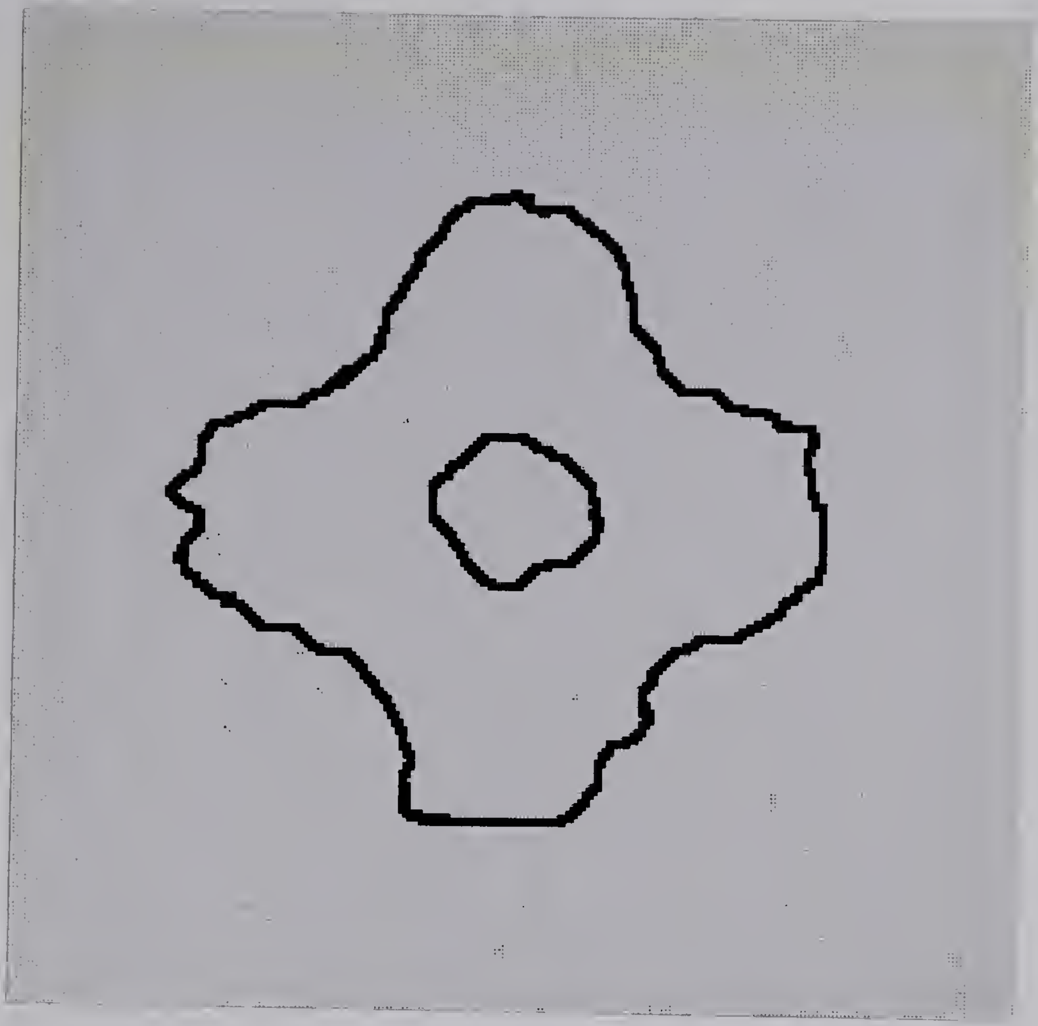

Figure 5.24 Test Picture #6 - Boundaries

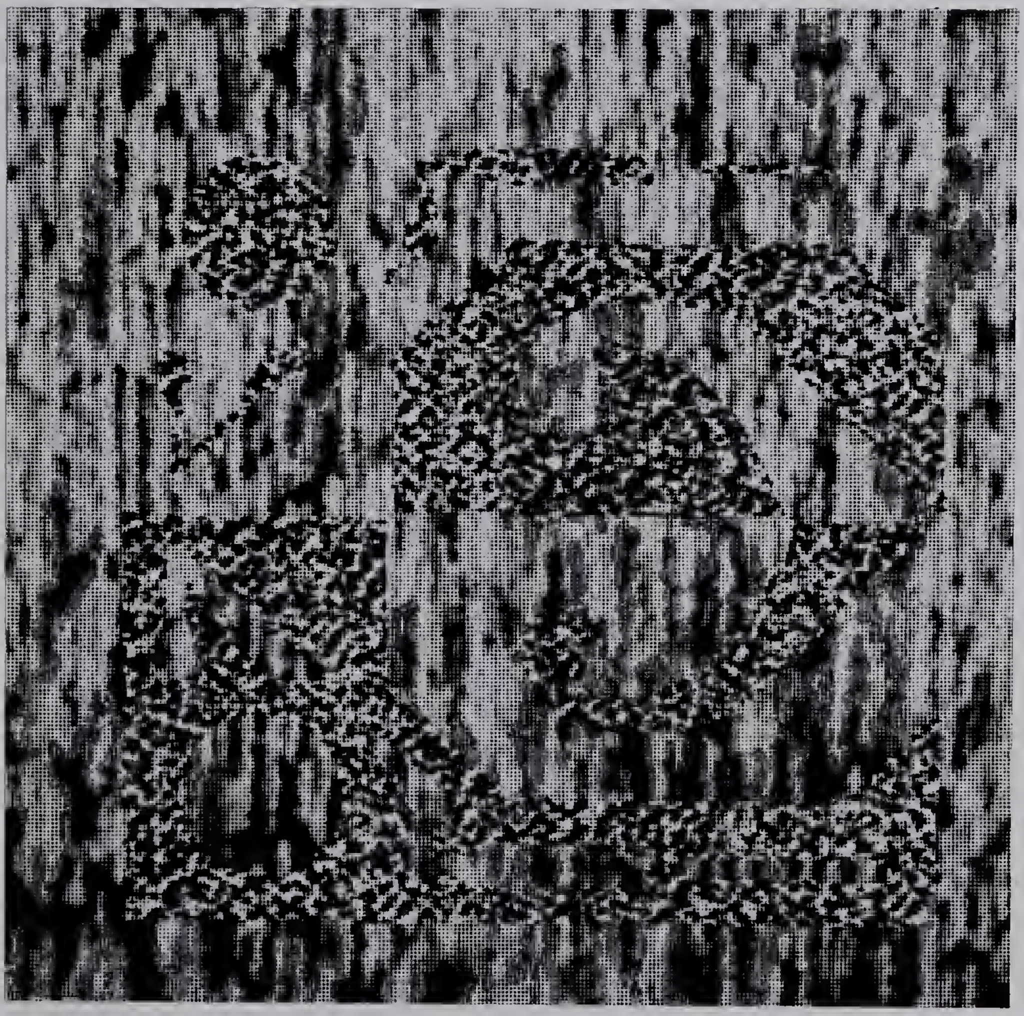

Figure 5.25 Test Picture #7

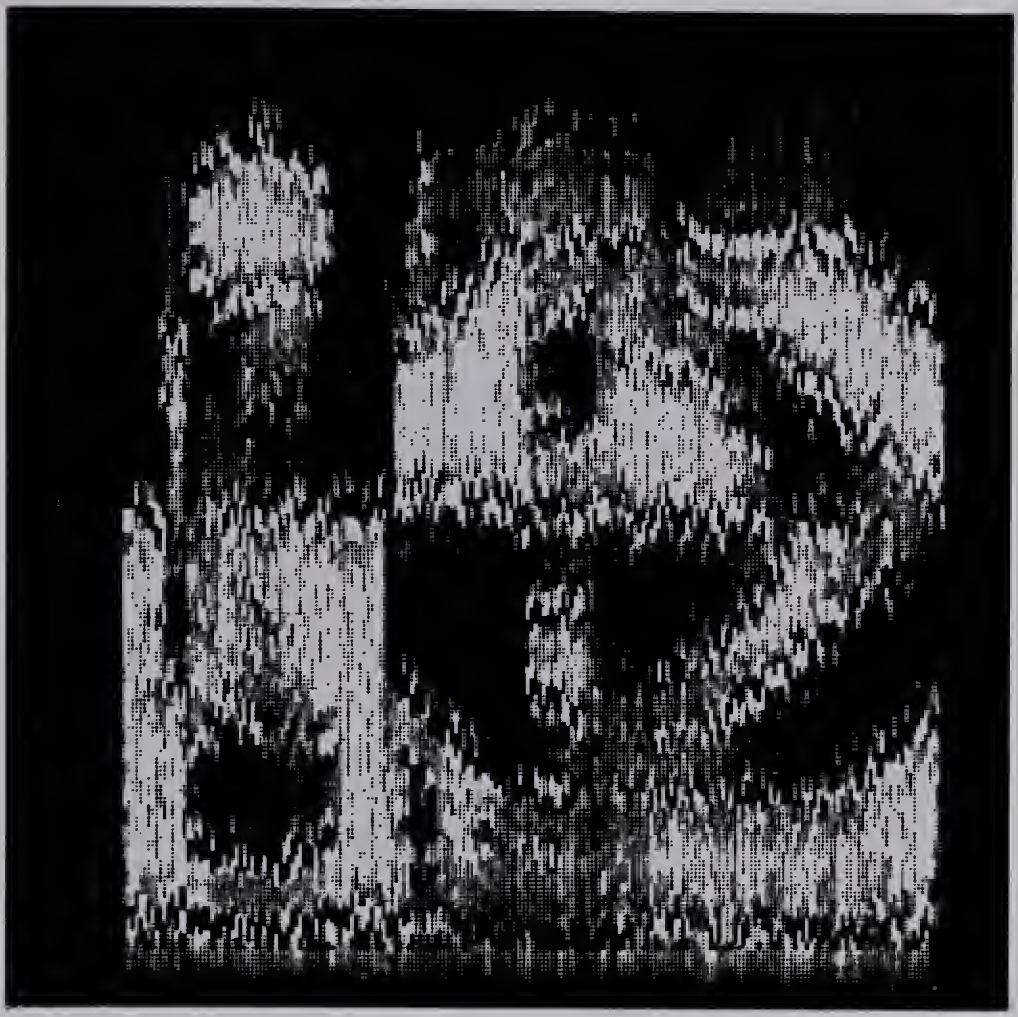

Figure 5.26 Test Picture #7 - Vertical C

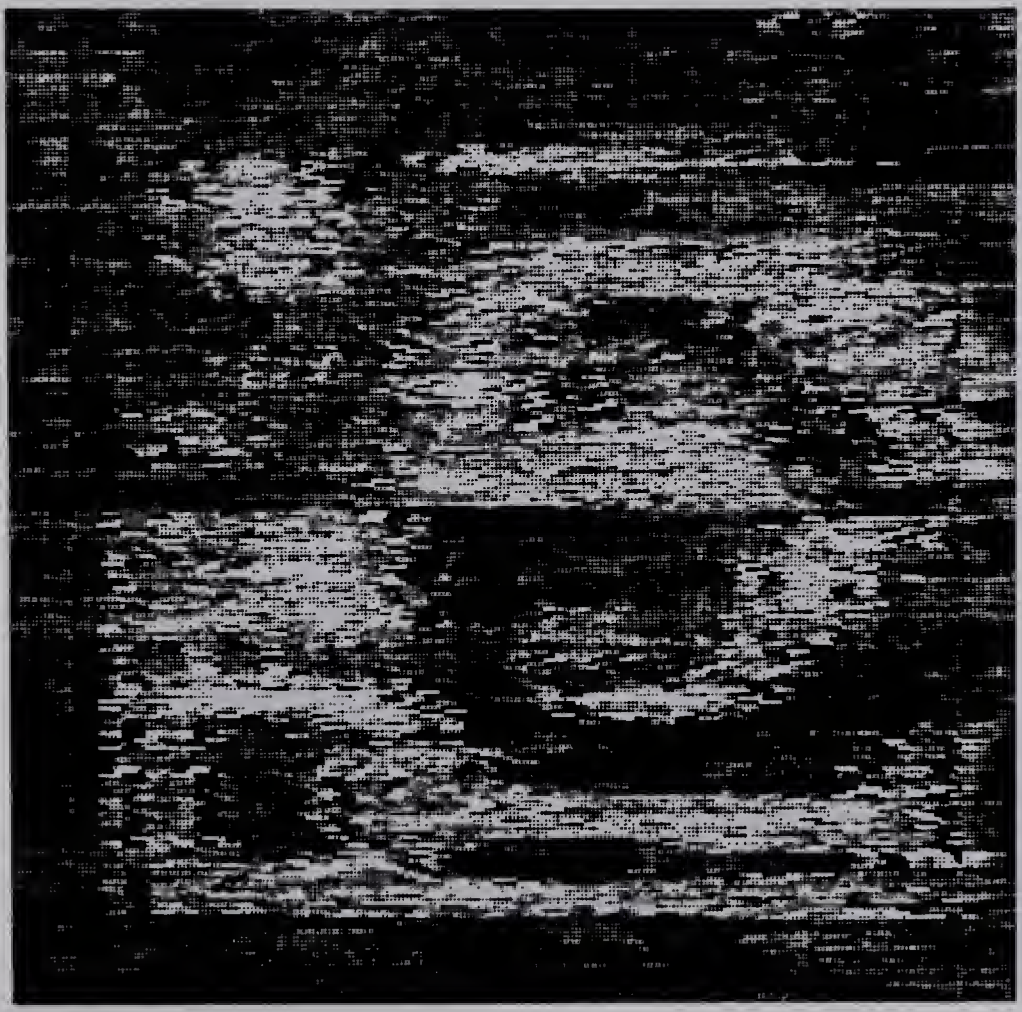

Figure 5.27 Test Picture #7 - Horizontal F

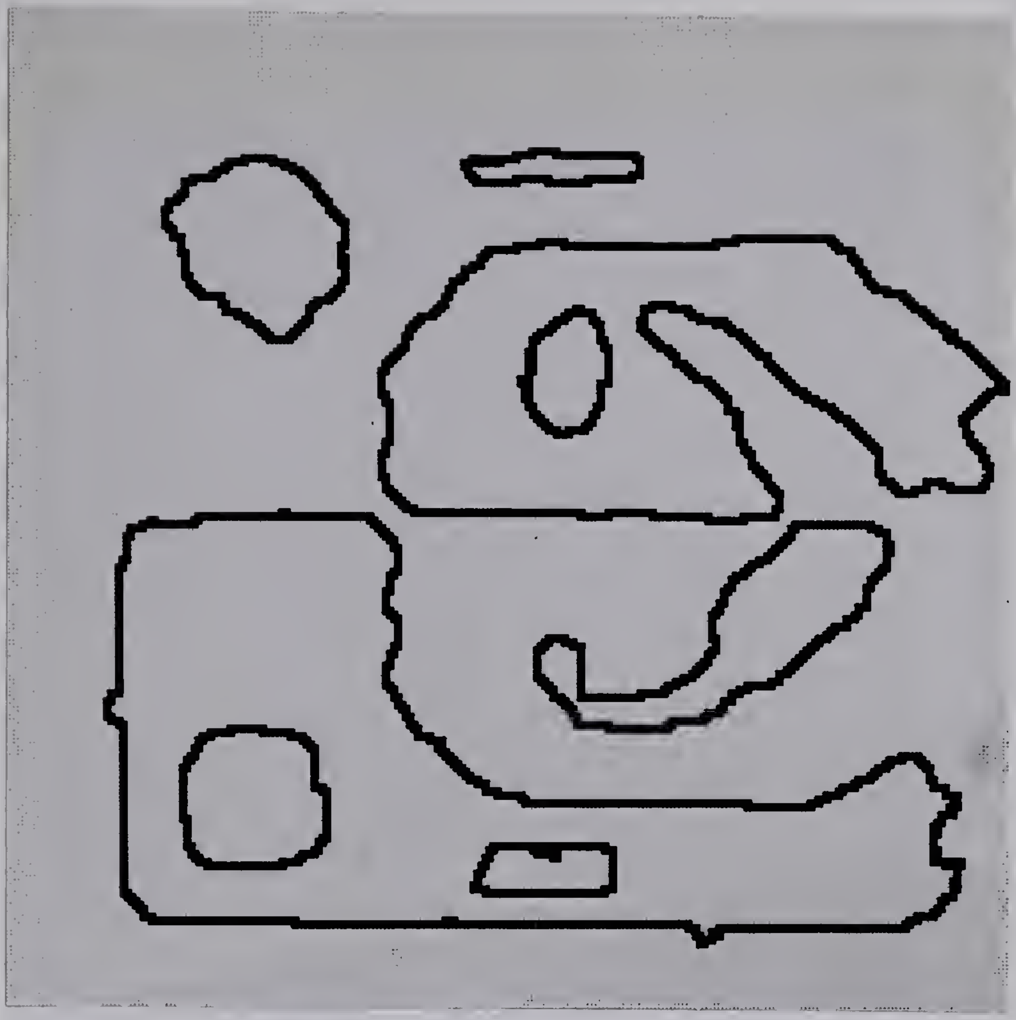

Figure 5.28 Test Picture #7 - Boundaries

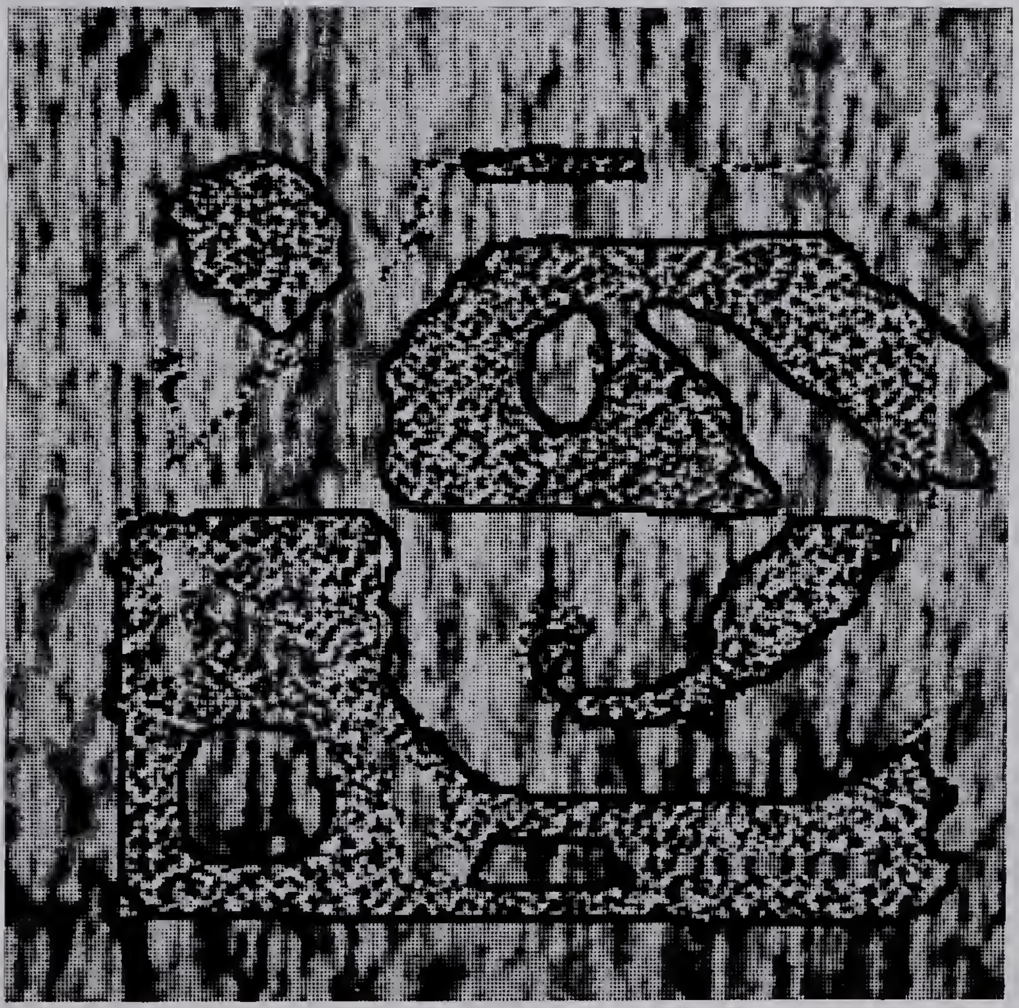

Figure 5.29 Test Picture #7 - Boundaries Overlaid

[illegible]

[illegible]

boundaries and the final boundaries overlaid on the original test picture in Figures 5.28 and 5.29. Finally is test picture #8, with boundaries overlaid, in Figure 5.30. This picture was produced from the background of test picture #4.

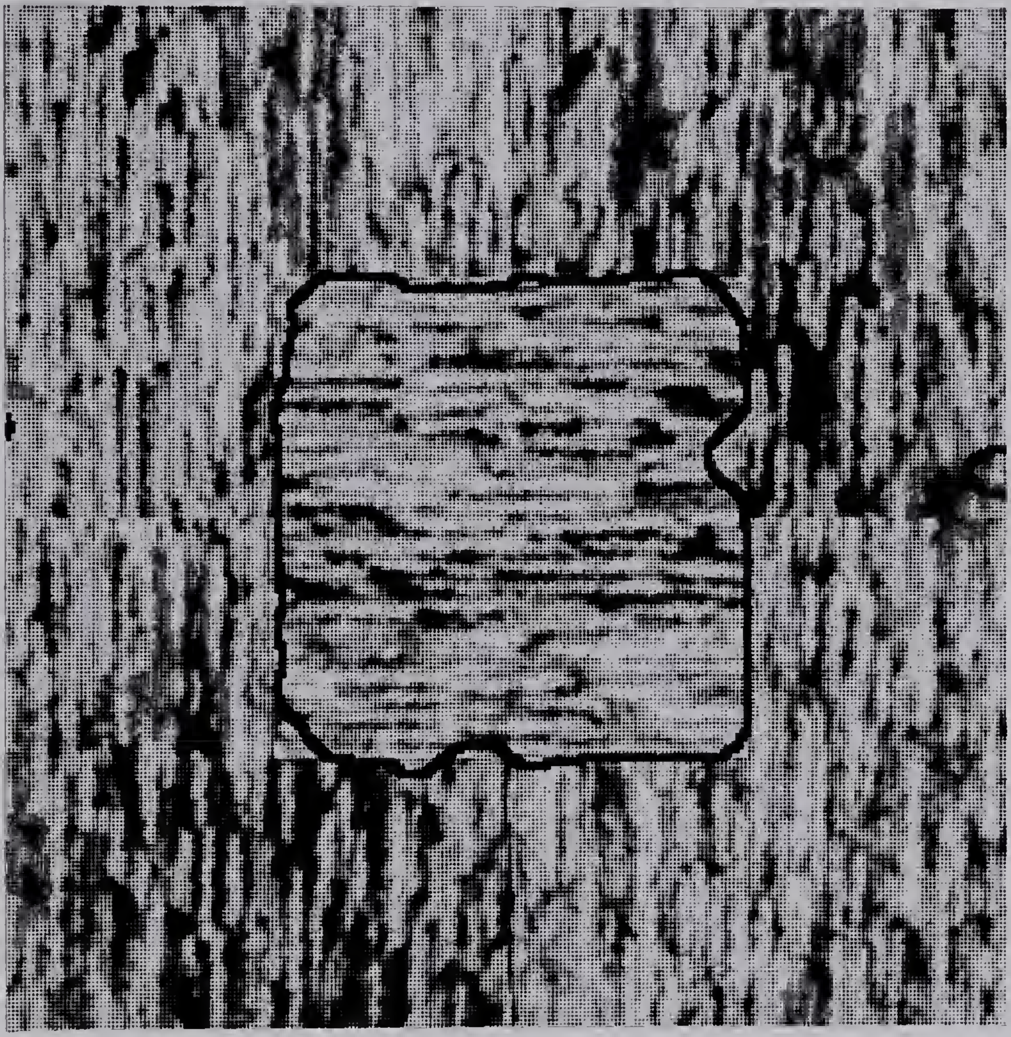

Figure 5.30 Test Picture #8 - Boundaries Overlaid

The background was segmented into four quadrants and the quadrants then repositioned such that discontinuities existed along the borders of the quadrants. The major portion of the original upper left quadrant was then rotated 90 degrees and centred in the picture. Both textures in this test picture are very coarse and only differ in orientation. This concludes the pictorial results.

Visually analysing the pictorial results, it can be

seen that, on the whole, the results are reasonably good, given that a local measure is being used. The boundaries for test picture #4 are fairly close to the best they could be. Deviations in the position of the resultant boundaries from the ideal position possible, are due to the fact that the natural textures used are very much more irregular in nature than the artificial test pictures. This irregularity makes it difficult to determine exactly when one type of texture stops and another one starts. Lack of texture uniformity is evident by the fluctuations present in the vertical F and horizontal C pictures presented. The boundaries for test picture #5 are no better than those obtained for test picture #4. In fact, the boundaries are slightly poorer. These results indicate that the enhancement and smoothing type of preprocessing performed to get this test picture is no substitute for a fluctuation threshold. The results do not, of course, rule out the use of other types of preprocessing.

The visual results from test picture #6 are similar in nature to those from test picture #4. The boundaries are fairly close with deviations from the ideal present due to the aforementioned reasons. In all three natural texture test pictures, the boundaries that should be present are present, though perhaps not positioned totally accurately. This is not true for test picture #7. The large relative size of the neighbourhood being measured, compared to the size of the textured regions and the proximity of the

regions to one another, causes some the the small regions to be missed and causes the boundaries of other regions to be distorted beyond what they might normally be. This accounts for the poorer boundaries for this test picture.

Attention should also be drawn to the rightmost boundaries produced, which in places extend towards the right side of the picture. This is caused by the procedure which handles measurements near the sides and corners of a test picture. As will be recalled from earlier discussion, the border procedure, used near the sides of a picture, locks the vector switching mechanism such that the measuring vector points away from the side being approached. In this case, it resulted in overlapped measuring or two regions being measured simultaneously. This caused further degradation of the final boundaries produced. In test picture #8 two very coarse textures are being measured relative to the size of the measuring vector (17 points). The resultant boundaries are a little poorer and the mechanism for controlling measurement near the edges of a picture mistakenly detects boundaries on the extreme left and right of the picture. In both cases this occurs where the texture is very flat, i.e., very little variation in grey level compared to the surrounding area. In addition, any discontinuities caused by juxtaposing similar textures are not detected. This lack of detection is to be expected when using a local statistical measure.

The results tabulated here, as those obtained from the artificial test pictures, confirm the visually results. The texture characteristics in Tables X, XI, XII, XIII, and XIV indicate that the different textures in a test picture are fairly well balanced in terms of average brightness and standard deviation. No special effort was made to do this, and it is probably a by-product of the automatic sensitivity control on the television camera which was used to digitize the images. The control automatically adjusts the sensitivity of the camera up if a scene is too dark and down if too bright. The measures based on spatial dependence matrices indicate that, on the whole, the textures can be distinguished from each other, though the textures in test picture #6 are not quite as dissimilar as those in some of the other test pictures. This is implied by two of the five measures (T1 and T3) which are very much alike in all orientations. Measures in the other textures may be alike, but usually not in all orientations. Of course, for test picture #6, this is to be expected since the two textures are basically the same except for degree of coarseness.

Again, information in the texture characteristics tables is confirmed by data in Tables XV, XVI, XVII, XVIII, and XIX, the secondary values tables. Depending on the orientation and the texture being looked at, measures F and C produce greater or lesser discrimination. A point to note is the MR values for test picture #6. These are all roughly the same in value, which is what should happen given that

Table X

Texture Characteristics of T.P. #4

T.P. #4	Background	Foreground
Name	coarse vertical woodgrain	finer horizontal woodgrain
Mean	31.51	32.65
S.D.	6.60	6.53
0 degrees		
T1	1038.1	1102.4
T2	19.644	13.697
T3	0.26260	0.30889
T4	2.6321	2.5450
T5	3.4146	2.7929
45 degrees		
T1	1037.6	1080.3
T2	21.021	57.125
T3	0.24644	0.14405
T4	2.6459	2.7842
T5	3.5715	6.1158
90 degrees		
T1	1045.0	1080.6
T2	6.0208	54.839
T3	0.42418	0.14575
T4	2.3882	2.7796
T5	1.8099	6.0065
135 degrees		
T1	1037.0	1078.8
T2	22.269	60.096
T3	0.23840	0.14020
T4	2.6562	2.7913
T5	3.6991	6.2771

The foreground texture is basically the same texture as the background, but reduced and rotated by 90 degrees.

Table XI

Texture Characteristics of T.P. #5

T.P. #5	Background	Foreground
Name	coarse vertical woodgrain	finer horizontal woodgrain
Mean	31.10	32.35
S.D.	6.57	5.55
0 degrees		
T1	1048.1	1108.5
T2	13.532	5.3598
T3	0.27096	0.42255
T4	2.5611	2.2972
T5	2.9637	1.7489
45 degrees		
T1	1047.5	1099.2
T2	15.159	23.059
T3	0.26119	0.22483
T4	2.5859	2.5813
T5	3.1134	3.8242
90 degrees		
T1	1053.6	1099.6
T2	2.9245	20.666
T3	0.52165	0.23292
T4	2.2387	2.5617
T5	1.2563	3.6324
135 degrees		
T1	1047.0	1098.3
T2	16.093	24.876
T3	0.25616	0.21706
T4	2.5960	2.5928
T5	3.2123	3.9694

This picture is a slightly enhanced and smoothed version of test picture #4.

Table XII

Texture Characteristics of T.P. #6

T.P. #6	Background	Foreground
Name	roofing shingle irregular	sandpaper irregular
Mean	29.46	29.01
S.D.	10.79	9.33
0 degrees		
T1	963.95	884.18
T2	40.775	88.460
T3	0.19906	0.11133
T4	2.9909	3.0655
T5	4.8826	7.7709
45 degrees		
T1	952.67	861.75
T2	63.732	134.19
T3	0.14906	0.09756
T4	3.0810	3.1217
T5	6.3247	9.3698
90 degrees		
T1	966.39	871.37
T2	36.514	114.68
T3	0.19389	0.10737
T4	2.9794	3.1071
T5	4.7408	8.6037
135 degrees		
T1	952.16	852.45
T2	64.719	152.84
T3	0.14562	0.09053
T4	3.0835	3.1306
T5	6.3887	10.044

The sandpaper is a finer blob-like texture than the roofing single which is also blob-like.

Table XIII

Texture Characteristics of T.P. #7

T.P. #7	Background	Foreground
Name	vertical woodgrain coarser	sandpaper irregular finer
Mean	32.52	29.07
S.D.	6.13	9.33
0 degrees		
T1	1084.6	886.53
T2	20.423	90.497
T3	0.24930	0.11007
T4	2.6015	3.0622
T5	3.5160	7.8503
45 degrees		
T1	1084.3	863.68
T2	22.100	135.67
T3	0.24293	0.09588
T4	2.6155	3.1142
T5	3.6508	9.4244
90 degrees		
T1	1092.7	874.10
T2	5.9177	115.52
T3	0.43151	0.10819
T4	2.3479	3.1005
T5	1.7812	8.6414
135 degrees		
T1	1083.9	855.21
T2	22.900	152.66
T3	0.22891	0.09120
T4	2.6223	3.1216
T5	3.7822	10.043

The background here is similar to the background in test picture #1 and the foreground is similar to that of test picture #6.
The background woodgrain texture for this test picture is coarser than the foreground sandpaper texture.

Table XIV

Texture Characteristics of T.P. #8

T.P. #8	Background	Foreground
Name	coarse vertical woodgrain	coarse horizontal woodgrain
Mean	31.51	32.65
S.D.	6.60	6.53
0 degrees		
T1	1038.1	1130.8
T2	19.644	6.7016
T3	0.26260	0.40417
T4	2.6321	2.3591
T5	3.4146	1.9237
45 degrees		
T1	1037.6	1120.9
T2	21.021	24.108
T3	0.24644	0.22782
T4	2.6459	2.6084
T5	3.5715	3.8559
90 degrees		
T1	1045.0	1122.0
T2	6.0208	22.146
T3	0.42418	0.25084
T4	2.3882	2.5895
T5	1.8099	3.5887
135 degrees		
T1	1037.0	1121.2
T2	22.269	23.507
T3	0.23840	0.23866
T4	2.6562	2.6040
T5	3.6991	3.7560

The foreground texture is the same as the background texture, but rotated 90 degrees.

Table XV

Secondary Values for T.P. #4

T.P. #4	Background PT = 22970		Foreground PT = 7056		MR
	Mean	S.D.	Mean	S.D.	
VTF	13.50	7.45	36.08	5.91	0.46
VTC	1.07	0.76	5.78	1.33	0.69
LDF	23.67	4.72	37.03	6.10	0.22
LDC	3.30	0.97	6.01	1.38	0.29
HTF	21.57	4.67	22.13	7.18	0.01
HTC	2.96	0.96	2.14	0.88	0.16
RDF	22.63	4.71	36.77	5.64	0.24
RDC	3.15	0.98	5.93	1.31	0.31

PTEX Program Parameters:
vector length = 17
fluctuation threshold = 2
other thresholds = chgth=6, ths=8,8

Table XVI

Secondary Values for T.P. #5

T.P. #5	Background PT = 22970		Foreground PT = 7056		MR
	Mean	S.D.	Mean	S.D.	
VTF	5.07	4.15	25.20	5.03	0.67
VTC	0.36	0.53	3.17	0.96	0.80
LDF	20.04	4.50	27.21	5.12	0.15
LDC	2.78	0.94	3.45	1.05	0.11
HTF	18.00	4.62	10.20	5.15	0.28
HTC	2.52	0.91	0.90	0.64	0.47
RDF	19.33	4.71	27.04	5.14	0.17
RDC	2.66	0.95	3.39	0.97	0.12

PTEX Program Parameters:
vector length = 17
fluctuation threshold = 2
other thresholds = chgth=6 ths=8,8

Table XVII

Secondary Values for T.P. #6

T.P.	Background		Foreground		
#6	PT = 10000		PT = 10000		MR
	Mean	S.D.	Mean	S.D.	
VTF	22.55	5.21	35.96	5.52	0.23
VTC	4.34	1.26	8.66	1.72	0.33
LDF	25.68	4.66	39.96	5.85	0.22
LDC	6.04	1.53	9.96	2.02	0.24
HTF	19.33	4.46	32.19	5.16	0.25
HTC	4.53	1.15	7.75	1.43	0.26
RDF	26.30	4.86	39.35	5.99	0.20
RDC	6.03	1.41	9.49	1.98	0.22

PTEX Program Parameters:
vector length = 17
fluctuation threshold = 2
other thresholds = chght=6, ths=8,8

Table XVIII

Secondary Values for T.P. #7

T.P.	Background		Foreground		
#7	PT = 10000		PT = 10000		MR
	Mean	S.D.	Mean	S.D.	
VTF	12.05	6.66	35.56	5.57	0.49
VTC	0.93	0.69	8.41	1.76	0.80
LDF	23.54	4.91	39.67	5.89	0.26
LDC	3.15	0.98	9.86	1.99	0.52
HTF	21.41	4.84	32.06	5.09	0.20
HTC	2.82	0.95	7.63	1.43	0.46
RDF	23.37	4.88	38.93	6.00	0.25
RDC	2.99	0.92	9.24	1.95	0.51

PTEX Program Parameters:
vector length = 17
fluctuation threshold = 2
other thresholds = chgth=6 ths=8,8

Table XIX

Secondary Values for T.P. #8

T.P. #8	Background PT = 22970 Mean	 S.D.	Foreground PT = 7056 Mean	 S.D.	 MR
VTF	13.64	7.30	22.98	4.29	0.26
VTC	1.10	0.75	3.29	1.02	0.50
LDF	23.97	4.77	24.27	4.41	0.01
LDC	3.40	1.00	3.47	1.01	0.01
HTF	21.86	4.57	15.50	8.20	0.17
HTC	3.06	0.97	1.20	0.82	0.44
RDF	23.10	4.58	24.55	4.45	0.03
RDC	3.22	0.98	3.61	1.02	0.06

PTEX Program Parameters:
vector length = 17
fluctuation threshold = 2
other thresholds = chgth=6, ths=8,8

Table XX

Boundary Comparison for T.P. #4

T.P. #4	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	1.9940	2.5329	2.2635
NEP	960	1186	0.2354

Table XXI

Boundary Comparison for T.P. #5

T.P. #5	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	3.5288	3.4239	3.4763
NEP	960	1076	0.1208

Table XXII

Boundary Comparison for T.P. #6

T.P. #6	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	1.9585	2.2359	2.0972
NEP	1604	1712	0.0673

Table XXIII

Boundary Comparison for T.P. #7

T.P. #7	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	8.3666	2.5450	5.4558
NEP	6359	4656	0.2678

Table XXIV

Boundary Comparison for T.P. #8

T.P. #8	Ideal to Final	Final to Ideal	SC Mean and NEPR
SC	2.1544	16.8252 (2.4164)	9.4898 (2.2854)
NEP	960	1153 (1068)	0.2010 (0.1125)

the two textures really only differ in resolution.

Visual subjective judgements are upheld by information in the boundary comparison tables listed as Tables XX, XXI, XXII, XXIII, and XXIV. All of the natural texture test boundaries are rated poorer than those produced for the artificial test sets. In the table for test picture #8 additional values are given in parenthesis. These are the values obtained if the false boundaries produced along the sides of the picture are ignored. These values indicate that the main boundaries created are quite reasonable in terms of position. Excluding the small false boundaries in test picture #8, the boundaries for test picture #7 has the largest SC mean value (5.4558) and has the worst observed boundaries. Test picture #5 final boundaries, derived from a preprocessed test picture, are not as good as those of test picture #4 (3.4763 to 2.2635). Boundaries for test

pictures #4 and #6 are rated very close together with #6 being only 0.1663 less, or better than #4. The main boundaries of test picture #8 are also rated very close to the boundaries of test pictures #4 and #6. Visually it is very difficult to judge which of the boundaries is the better and the SC mean value may not be accurate when dealing with such small differences. As was seen with the artificial results, the NEPR values are poor indicators of boundary goodness. The next chapter discusses results presented in the current chapter, offers conclusions, and presents for thought some future work which may be accomplished.

CHAPTER 6

CONCLUSION

In defining local picture measures, employed for finding boundaries in textured images, certain criteria were used. These criteria were (1) that measures should be few in number and relatively simple in terms of computation since they would be applied many times, (2) that the measures should operate directly on the points in a picture, (3) they should be orientation dependent to preserve directionality information, and (4) they should attempt to determine inherent characteristics in a texture. The measures determined, using these rules as a guide, were used to analyse textures and produce 2nd-order pictures with reasonably good results.

Final results show that the more regular a texture, the better the boundaries produced and that there is a tendency for regions which are small in size, compared to the size of the measuring neighbourhood, to give rise to poor or nonexistent boundaries. Small regions also tend to influence the determination of boundaries for other nearby regions. This is because the small regions cause multiple

measuring to occur, i.e., more than one region being analysed at a given time. Difficulties also arise when trying to find boundaries near the sides of a picture. The procedure which handles measuring near sides and corners of a picture is slightly different than the one concerned with the main central portions of an image. Thus boundaries near the sides of a picture can be distorted due to the different handling procedure (as seen in test picture #7). A further influence on boundary determination is the effect of the vector switching mechanism used, i.e., switching of measuring from a vector on one side of a point to the other side. Given regular textures the switching is crisp and clean, but with poorer and more irregular textures switching becomes confused and tends to oscillate even when thresholds are increased to take into account the greater irregularities.

A beneficial point of scanning in different directions is that information which may be missed in one direction can be detected when scanning in a different direction. Thus different information can be combined, from various pictures, to produce a final picture. In addition, performing multiple scans of a picture and measuring texture characteristics with a different vector length each time, can bring out slightly different information. The combining of this information, which individually may be weak, will then produce information with greater strength, e.g., more distinct regions in an image.

Preprocessing of pictures, e.g., as used for test picture #5, tends to be ineffective, giving similar or poorer results compared to those obtained from non-preprocessed pictures. The preprocessing method used reduces the picture contrast and any strong, quick rise and fall of grey level values is adversely affected.

The results for test picture #8 indicate that discontinuous boundaries produced by juxtaposing similar textures cannot be detected using the local measures that were defined. This is understandable since the detection of these borders requires global or contextual knowledge. Also from this test picture it can be seen that performance degrades as the texture becomes very large compared to the size of the measuring neighbourhood, as evidenced by slightly poorer boundaries compared to test picture #4 and false boundaries produced on the extreme left and right side of the picture.

Measures in the tables given indicate that spatial dependence matrix based measures are beneficial in determining dissimilarity between different textures and also in classifying textures. Some poor aspects of spatial dependence measures include, at times, difficulty understanding what exactly is being measured and the fact that they are derived from matrix values rather than directly from textured grey level values. Looking at the entries in the secondary values table, there is a

substantial amount of fluctuation in values produced for natural textures. This is indicated by several relatively large standard deviations as well as visually by inspecting the 2nd-order pictures. The MR (mean ratio) value, while simple in nature, is useful in quickly pinpointing measures and orientations which indicate good distinction between two textures. The SC values in the boundary comparison tables are valuable in that the SC mean value agrees with what visual judgement predicts should be true. Also, the difference between SC values for the ideal to final and final to ideal comparison indicates whether any boundaries have been missed or falsely produced. The more similar these two values, the better. As an example, test picture #7, which has poor boundaries has SC values 8.3666 and 2.5450 for ideal to final and final to ideal comparisons, while test picture #6 with amoung the best boundaries, has respective SC values of 1.9585 and 2.2359.

6.1 Further Work

There is great potential for other direct texture measures to be defined similar to, or based on, the measures used in the current work. One of the measures used is described by a simple finite state machine. This implies that other measures could be described or defined by finite state machines which are more elaborate than the present one. Advantages of using this approach are that the measures are clear in function and a certain amount of

decision making is added to the local measure. Thus decision making in the main procedure can be transferred to the local measuring algorithm. Whatever the measures used though, attention should be on determining characteristics of a texture, rather than generating numbers and responding to them, i.e., the measures are looking for properties or conditions which are inherent in texture.

The use of a mechanism or procedure to control the switching that indicates which vector of points about a central point, is to be used for measuring, implies that a variable shaped neighbourhood is being applied to a picture. If the vectors used for each orientation are overlayed on one another, then at different locations in a picture, vectors or arms of the neighbourhood stretch in different directions, depending on previous knowledge. This idea can be extended such that neighbourhoods are also of variable size, i.e., the vector lengths change in size depending on the amount of information present. If it is judged, according to the frequency measure of a picture, that a large amount of information is present, or the information is becoming more dense, then a smaller vector length can be used until the quantity of information starts to fall off, after which the vector length starts to grow. There would, of course, be some maximum and minimum length on the size of the vectors.

One problem with using variable size vectors, as in the

present method, is what to do when the edge of a picture is approached. This problem is aggravated with the use of variable size vector lengths. With regard to the switching of measuring, from a vector on one side of a point to the other side, more information is required and better decision criteria is needed to decide when to switch and when not to switch. More prior knowledge could be used in deciding when to switch, i.e., use of information from several prior decisions. In some cases, when obtaining a value, the measuring vector could be situated symmetrically about the point of interest. In other cases, comparing the values obtained from vectors on each side of the main point and from nearby neighbourhoods would be informative. Depending on the circumstances, being able to backup and remeasure points, could produce better results.

Another aspect is the further development of manipulation processes for 2nd-order pictures. In the work presented here, each step in the manipulative sequence was, on purpose, relatively simple. There is potential, though, for devising other ways of using 2nd-order pictures, e.g., higher level processing could produce better boundaries by taking into account the Gestalt priciples that humans use. The word Gestalt being used to describe a general grouping of shapes to produce recognizable figures, e.g., a staight line, a square, or a circle. Further work can also be accomplished in regards to rating results and in determining how different two textures must be if results are to be

adequate. This work could be facilitated by that of Zobrist and Thompson [1975] who have developed a distance function for textures which compares favourably with how humans judge textures. Of course, there should be a limit to how sensitive a texture measure is to differences in texture. A texture measure which is too sensitive would judge an irregular texture which possessed gradual variations in pattern repetition or overall brightness to be several different textures rather than one.

Further in judging the process presented here, an artificial test picture could be used and various amounts of noise added to see what the effect is on the final boundaries produced. In trying to very accurately grade boundaries created, other measures of boundary goodness, besides the one given here, should also be used. Ideally, the best measure of goodness would be achieved by following, what is hoped, the same boundary in different pictures and measuring how much deviation there is between the boundaries.

Finally, the textural boundary finding procedure should be expanded to textured scenes which contain multiple textures, i.e., more than two. With multiple textures, problems arise in handling regions in the 2nd-order pictures which differ in average brightness, but which also possess a great deal of grey level fluctuation. Work in this area could be aided by that of Rosenfeld, Lee, and Thomas [1970],

for example, with their detection of "conspicuous" edges.

In closing, while satisfactory results have been produced for certain cases, there is much more research which can be accomplished in this area. This further research basically encompasses devising better measures, applying the measures with more decision making criteria, and processing the results of the measures with higher order or more holistic methods.

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APPENDIX A

HARDWARE/SOFTWARE

This appendix discusses the computer hardware and software aspects relating to the thesis. Included is a description of the hardware used, how it was used, and why it was used. In conjunction to this, software available is also discussed. This is followed with a list describing the function of relevant programs which were implemented in the course of the thesis.

Two basic hardware/software systems are used for the generation of data and the implementation of programs. One is the University of Alberta, Department of Computing Science's DIgital Picture Processing System (DIPPS) and the other is the central computing facilities provided by Computing Services at the University of Alberta.

The first of these two is made up of a Digital Equipment Corporation (DEC) PDP-9 with various attached peripheral equipment. For the most part, this consists of a teletype, CRT terminal, Tektronix 611 storage scope, Sykes cassette, TV camera, quantizer, and an attached colour display system. The colour system containing a colour video

monitor, Hughes Model 639 H scan conversion memory, and four bit slice microprocessors, where each micro handles a four bit slice to make a sixteen bit word. A picture may be input to the system by means of the TV camera and quantizer. The picture is digitized into 64 grey scales and stored on a specifically allccated "picture" disk. A stored picture may be displayed on the 611 scope or on the colour TV monitor.

Display on the scope can be in one of two modes. In the first (storage mode) grey levels are generated by illuminting a variable number of dots in an 8 by 8 matrix. The second means of display is accomplished by modulating the intensity of the scope's cathode beam while the device is in write-through mode. In this case, it is necessary to photograph the beam in order to build up a visable picture. While this procedure produces good quality image output, it is also very slow.

In the colour system there are four bit slice Monolithic Memories 670 microprocessors [Sherrard and Davis, 1978]. This system produces 16 levels of intensity for the three colours red, green, and blue. These three colours can then be combined to produce other apparent colours. Different levels of brightness are created on the TV monitor by varying the intensity of the cathode beams. The advantage of colour output is that it allows for greater discrimination and separation of detail since the human eye is more sensitive to changes in colour than to changes in

grey level intensity.

The software operating on the PDP-9 is a modified version of the manufacturer supplied Keyboard Monitor [Huneycutt and Newman, 1975]. One modification has been to allow the envokation of a Picture OPerating System (POPS) [POPS User's Manual]. POPS processes commands and loads programs which allow one to take a picture, display a picture, determine histograms, and perform some picture manipulations and operations such as linear grey scale transformations and gradient edge detection.

DIPPS has certain hardware and software limitations which are to some extent interrelated. The main limitation is the small amount of main storage, the quantity of memory being 8 K words, each word 18 bits long. This amount of memory makes it very difficult to design large programs and/or process large amounts of data. Due to memory constraints, the only practical programming language available is the machine assembler language, implemented under the name MACRO-9. Use of MACRO-9 does not readily allow for smooth implementation of programs. A further consideration, when using the PDP-9 over an extended period of time is reliability. Certain components of the system are comparatively old and the question of hardware dependability must be kept in mind. Taking into account the above facts and potential problems it was decided to use the PDP-9 in a picture digitizing or data gathering role and to

use the main university computing facilities for processing and display. By means of a communications link it is possible to take pictures stored on the PDP-9 and transmit them to the main computer (and vice versa) where they can then be operated upon and displayed.

Within the main computing facilities, a number of hardware and software components are available. The system itself is comprised of an Amdahl 470 V/6, possessing a large amount of memory, and running under the Michigan Terminal System (MTS). The devices of significant importance to image processing, which are attached to the computer, are the line printer and Varian Statos 4211 electrostatic printer/plotter. Both of these devices can be used for picture display, with the latter favoured due to its greater quality and resolution, it being able to generate points two-hundredth of an inch apart. Grey scales are created on the line printer by overstriking characters and on the electrostatic printer/plotter by filling in points in an 4 by 4 or 8 by 8 matrix. One disadvantage of the printer/plotter (at least with this particular one) is that electrostatic charge is not always placed uniformly on the paper. The result is vertical banding, most noticeable in very dark regions where greater or stronger amounts of charge have been deposited. While this is not very desirable, it is not an insufferable problem when displaying pictures.

The greatest advantage of the MTS system is its command language and system programs, which allow users to run programs, edit and manipulate files, and output information to devices in a straightforward manner. Also a number of programming languages are available under the system. The main one used (with regard to the work done here) was ALGOLW. This language allows byte manipulation, stream I/O, and dynamic storage allocation. These latter two points are important when working with pictures of different sizes. It allows one to read in variable length records and allocate adequate (and not excessive) storage for a picture. This language also permits structured programming, an important factor for its use.

Pictures in the system were stored in files, either line files or sequential files. A line file allows one to selectively access individual lines or records in the file. Sequential files store information one record after another from beginning to end and do not allow random access of records. While sequential files are not as convient as line files, they are more efficient in terms of amount of memory needed for storage (being less than for line files) and amount of time (also less) needed to perform input/output operations. A picture in either a line or sequential file is packed one pixel per byte and each picture consists of N rows and M columns. Each row of the picture is one record (line) in the file and each record (line) is M bytes long. The picture may be preceded in the file by a header record

(55 bytes long) which is primarily useful for the information it contains on the number of rows and columns in the picture.

Prior to this work no programs existed for picture manipulation on the main system, thus it was necessary to develop a number of programs, many of which are not directly related to the theme of this thesis. Following is a list of some of the more relevant programs which were implemented. The list contains the name of the program and a brief explanation of its function.

PALG - this program allows one to algebraically combine two or three similarly sized pictures together in various manners. It is possible to add the pictures together, subtract one picture from another, or to average the pictures together.

PCAT - to concatenate any number of pictures or portions of pictures together. It is possible to overlap portions, with a subsequent specified portion overwriting a previous one.

PDIS - to interactively display a picture on a terminal. Different characters are used to represent the different grey levels.

PEDCNT - tabulate the number of edge points in a binary edge picture. Presents tabulated and percentage results.

PED1 - edge detection program number 1. Finds edge by

simple gradient method. Edge exists if MAX-MIN >= threshold in a specified cross shaped area.

PED2 - edge detection program number 2. This program finds edges in a manner similar to program PED1, except in this case, it is done by determining the difference between the maximum and minimum elements in a rectangular neighbourhood about each point in the picture. If the difference is greater than or equal to some threshold value, then an edge point is said to exist at the spatial location of the central point of the rectangular neighbourhood and a binary 1 is output by the program (otherwise a binary 0 is output). The size of the neighbourhood region can be specified by the user (default is a three by three square), as well as the threshold value.

PEXP - expands a picture four-fold by first flipping it over rightwards and then flipping the results of this downwards. Can think of this as similar to unfolding a piece of paper which has been folded in half twice, each fold at a right angle to each other.

PIC1 - will display a picture on a line printer using overstruck characters to produce 36 levels of grey.

PIC3 - picture display for Varian Statos 4211 electrostatic printer/plotter. Can generate 64 levels of grey and display pictures in various manners with either linear or logrithmic output.

PLINK - reads in a specified number of edge pictures and

links or combines them together to produce a single resulting binary picture. Combines pictures logically or by means of a threshold, where if N or more input edge points exist for a given spatial location then an output edge point is produced.

PLOTH - grey scale distribution plot program. Produces a labelled plot on either a Tektronix storage scope or Calcomp plotter.

PMGEN - reads in a picture and produces a binary mask by means of a threshold. If pixel value is less than some threshold then zero is produced else a one. This resulting picture may be used as partial imput to the program PMSEL.

PMSEL - combines two pictures together by means of a binary mask picture (see PMGEN). Depending on whether the value in the mask picture is 0 or 1 selection will be made from one or the other of the pictures to be combined. By choosing some portions from one picture and other portions from the other picture, a new picture is generated.

PREDS1 - will reduce the size of a picture by a factor of N. This is done by choosing every N'th element row-wise and column-wise.

PSDM - calculates the four spatial dependence matrices and five statistics based on the matrices.

PSM1 - smoothing program number 1. Inspects the four neighbours N about each point P (above, below, left, and

right) and classifies these points as being either similar to the center point or as being different according to following criteria: if ABS(N-P) <= threshold then the point N is classified as being of the "same" class, else it is included in the "other" class. The average of the class with the largest number of elements is used to replace the central point.

PSM2 - smoothing program number 2. Replaces the central point with the average of a cross area up, down, left, and right of the point being looked at. Dimensions of the cross area is user specified.

PSM3 - smoothing program number 3. Replaces a point by the average of the rectangular neighbourhood surrounding the point. Dimensions of the rectangle are user specified.

PSM4 - similar to PSM1, but uses a rectangular region as in PSM3 instead of a small cross shaped region.

PSTAT - calculates statistics and histogram concerning the grey levels within a picture. Output is designed for a terminal or a line printer.

PTEX - program to analyse a textured picture and generate eight 2nd-order texture pictures. There are two pictures (a frequency picture and a contrast picture) produced for each scan direction made: vertical (90°), left diagonal (135°), horizontal (0°), and right diagonal (45°).

PTGEN - generate a picture consisting of artificial textures. A rectangular pattern consisting of the grey

scales 0 to 63 is provided to the program (by the user) and is then repeated (a user specified number of times) down and across.

PTRAN - performs a linear transform on a picture. May specify N linear transformations, each transformation being applied to a window of the picture. Subsequent specified transformations and windows may overlap previous ones.

PTRP - will transpose a picture. Tranposed picture can be reduced at the same time by selecting every N'th row and column. Picture may also be reversed or not as wished.

PT3 - reformats a picture which has been transmitted from the PDP-9 to MTS. Picture is reformatted into row-wise format, one pixel per byte.

PTXS - calculates secondary values tables entries.

PWIN - allows one to window out a portion of another picture.

P8TO6 - will convert a with 8 bits per pixel into a picture with 6 bits per pixel.

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